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The Geography of Worker - Firm Sorting: Drivers of Rising Colocation

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Abstract: Using social security data and an AKM wage decomposition, this paper examines spatial wage inequality in West Germany. Spatial inequality in log wages rose sharply between 1998 and 2008, driven largely by stronger positive spatial assortative matching between workers and establishments, i.e., colocation. Changes in establishment wage premia were largely unrelated to rising colocation, while labor mobility reduced it. Instead, growth in worker pay premia among stayers was concentrated in regions that already had many high-wage workers and establishments, amplifying pre-existing patterns and leading to "colocation without relocation." Germany's rising trade surplus raised stayers' pay premia in precisely these regions and quantitatively accounts for the observed increase in colocation, pointing to trade as an important mechanism.

JEL: J31, J61, R23

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1. Introduction

A well-documented pattern is the concentration of highly skilled workers in economic "hotspots" often associated with higher productivity, wages, and opportunities coexisting with lagging regions falling permanently behind. This trend has triggered widespread concerns about regional divergence and the potential erosion of economic and social cohesion especially in the context of "brain drain" effects, as prominently discussed, for instance, by Moretti (2012) for the United States.

With the increasing availability of linked employer-employee data, the literature has recently moved from juxtaposing a region's share of college workers with the region's wage level towards the analysis of the covariance of fixed effects from log wage decompositions in the spirit of Abowd et al. (1999, henceforth AKM). More precisely, colocation is defined as the between-region covariance of worker fixed effects and establishment effects (Dauth et al. 2022; Card et al. 2025). The core advantage of the AKM setting is that worker effects are purged of employer pay-setting influences and vice versa. When studying regional inequality, this approach ensures that worker effects are not confounded by the regional wage level and, similarly, that the regional wage level is not merely the consequence of worker heterogeneity across regions.

Still, we know very little about the timing, the precise mechanisms and the economic reasons for rising colocation. Much of the existing debate attributes rising colocation to sorting mechanisms involving reallocation of workers: skilled workers moving towards agglomerations, which creates agglomeration effects (Diamond 2016) including better firm-worker matching (Dauth et al. 2022). However, there may also be other mechanisms that increase colocation, and different mechanisms may have very different consequences for regional development and society. For instance, colocation can also intensify without large-scale worker mobility through mechanisms such as changing employer pay policies or shifts in skill premia reinforcing pre-existing inequalities. In such cases, lagging regions retain their skill base, which on the one hand may ease future convergence but on the other hand also hints on untapped aggregate productivity potential when worker skills and firm productivity are complements in production or agglomeration forces are generally important in knowledge-intensive production (Moretti 2012).

This paper aims to improve our understanding of rising between-region wage inequality by focusing on the spatial sorting of high-wage workers to regions hosting high-wage firms and low-wage workers to low-wage regions - referred to as colocation. Using AKM decompositions for a representative sample of West German full-time workers, we separate establishment and worker effects. As discussed in Card et al. (2025), it is important to compute place effects from appropriately aggregated establishment effects rather than estimating place effects directly, and we follow this approach. We first document that increasing colocation explains a substantial share of the rise in between-county wage inequality. The main objective of the paper is to document in detail the timing and the mechanisms of rising colocation. Equipped with this knowledge we are then able to identify one major economic force triggering the rise of colocation.

We find that the rise in between-county wage inequality mainly occurred between 1998 and 2008, with little increase before and even a slight decline thereafter. The rise in colocation narrowly follows these trend patterns and explains 40% of the rise. Importantly, the rise in colocation was primarily a sudden and sharp reinforcement of *pre-existing colocation*. We show that this rise in colocation is not driven by changing employer pay policies. Instead, changes in worker effects play the central role. Colocation stems mainly from differential growth in worker pay premia among stayers, while labor mobility – which includes both cross-county moves of incumbent workers as well as labor market entry and exit – reduced colocation. Growth in worker pay premia was strongest for high-wage stayers in initially high-paying counties but negative for stayers in initially low-paying counties, thereby strongly reinforcing pre-existing colocation. The overall outcome in West Germany is thus probably best described as 'rising colocation without relocation'. The U.S. evidence does not match our exact approach – there is, for instance, no study on colocation using AKM fixed effects – but its findings are interpreted as being driven by mobility (Moretti 2012, Diamond 2016). Thus, although colocation increased in both West Germany and the United States, the underlying mechanisms differ markedly.

Turning to the economic forces at play, we note that the relevant period was characterized by a tremendous rise in trade integration of the German economy due to both the rise of China as a global exporter but also the fall of the 'Iron Curtain' and the subsequent opening of Eastern Europe to trade (Dauth et al. 2014). Germany was able to benefit from integration via strong export growth. We will review economic theory and empirical evidence and demonstrate that increased export opportunities are expected to lead to exactly the colocation patterns we observe: i.e. exports will exacerbate pre-existing colocation via self-selection of high-wage regions into exporting and rising worker effects in high-paying regions. We interpret trade integration as a theoretically plausible and empirically well-aligned mechanism, while recognizing that it need not be the only force behind the rise in colocation.

We then demonstrate empirically that the increase in export activity (primarily to Eastern Europe), indeed originated in counties with high ex ante AKM establishment effects and more than fully accounts for the observed rise in colocation. This effect operates precisely by raising worker effects of high-wage workers, in particular among stayers, but not those of low-wage workers. Thus, the rise of Germany as a dominant exporter substantially contributed to spatial inequality and strengthened colocation patterns by driving up (high-skilled) workers wage premia in regions that already offered high establishment wage premia and hosted high-wage workers. Conversely, theory predicts falling labor demand in import shocked counties. The implications for colocation thus depend on whether import shocks are concentrated among initially low paying or initially high-paying counties, which is, unlike in the case of exports, theoretically uncertain. Our empirical results show that imports were concentrated in initially high-paying counties, too, did reduce worker effects, and, consequently, import growth did reduce colocation.

In sum, the export channel dominated in Germany, and therefore trade integration increased colocation. Differences in trade patterns help explain why the mechanisms behind rising colocation differ starkly between Germany and the United States. In Germany, export growth was concentrated in already high-paying regions, raising skill demand there. As a result, rising colocation did not rely on spatial mobility of workers. In the United States, by contrast, work by Moretti (2012) and Diamond (2016) implies that structural labor-demand shifts induced highly skilled workers to move toward high-wage locations.[2]

Our work primarily adds to the literature on spatial inequality and sorting by exploring the evolution of colocation, i.e. timing and precise mechanisms, and the economic forces leading to it. Diamond (2016) observes that college graduates increasingly sort into large cities in the U.S. and concludes that local productivity shocks – coming from a shift-share analysis of changes in nationwide industry-level wage levels and local industry composition – ignited the sorting process at some point in time between 1980 and 2000. Rising housing costs in cities with a high college share then resulted in out-migration of low skilled workers. While rising colocation is documented in the seminal paper by Diamond (2016), timing, mechanisms, and

[2] Whereas Autor et al. (2013) find little evidence for migration responses across U.S. regions following the steep increase in Chinese imports, Greenland et al. (2019) report population declines after import shocks as do Autor et al. (2021). Effects seem to be concentrated among younger, foreign-born workers.

economic forces all differ from our setting: the period of analysis largely predates ours, mechanisms leading to colocation are based on worker mobility (which is unimportant in our data), and international trade is an unlikely reason for migration as the period of analysis ends before the China shock and the rapid increase in international trade.

Combes et al. (2008) document spatial sorting for France analyzing high-wage workers and places and confirm colocation. They do not explore the evolution of this sorting over time, nor do they aggregate place effects from establishment effects (cf. the critique in Card et al. 2025). Dauth et al. (2022) document some empirical facts on rising colocation for Germany and use AKM wage decompositions but then focus on within-county sorting whereas we analyze between-county sorting. They do not analyze the role of trade integration for spatial sorting.[3]

We also add to the literature on the effects of trade integration on within-country inequality. Our results confirm predictions in Helpman et al. (2010) for the German context. Specifically, we show that colocation pre-dating trade integration will be reinforced by export growth because high-wage employers will enter export markets (Melitz 2003), which leads them to further upgrade their workforce and to raise wages of their already high-paid workers even further. We also find support for the core idea in Autor et al. (2013) by showing that import-shocked local labor markets see a wage decline and we add to this by showing that this is primarily transported via a decline in AKM worker effects and only a small decline in employer effects. We further show that this happened within labor markets hosting initially highly-paying employers thereby lowering colocation.

The paper proceeds as follows. We first describe the data and empirical framework. We then document the rise in colocation, focusing on its timing and underlying components, in particular the distinct roles of worker and establishment wage premia. These descriptive patterns narrow the initially broad set of potential explanations and discipline our subsequent analysis of mechanisms. We then focus on international trade, not as the only possible explanation, but as a theoretically plausible and quantitatively important candidate mechanism that fits the empirical patterns particularly well.

[3] For an early and insightful attempt, see Mion and Naticchioni (2009). They apply an AKM decomposition to study colocation but note that their sample is too small for a reliable AKM estimation. They therefore focus on a specification with worker fixed effects and firm size instead of firm fixed effects.

2. Data

We utilize the Sample of Integrated Labour Market Biographies (SIAB), a linked employer-employee panel provided by the Institute for Employment Research (IAB). The SIAB contains a 2% random sample of the employment biographies of all individuals subject to social security contributions in Germany and provides daily records on earnings and, among others, information on age, gender, place of work, and employer identifiers.

Following Stüber et al. (2023), we deflate and impute daily earnings[4] and restrict our sample to employment spells that include the cutoff date of June 30 in each year. Furthermore, we limit the analysis to regularly employed, full-time workers aged 20-59 to align our analyses with the sample restrictions of the AKM procedure described below. We further restrict the sample to workplaces located in West Germany between 1985 and 2021.[5] The SIAB data does not include precise information on hours worked. However, since we focus on full-time workers, we use the term daily wage (or simply wage) instead of daily earnings throughout the analysis.

A key feature of our study is the decomposition of individual wages into establishment-fixed and worker-fixed effects (or "AKM effects"), as pioneered by Abowd, Kramarz, and Margolis (1999) and applied by Card, Heining, and Kline (2013, henceforth CHK) to the German data. Bellmann et al. (2020) provide these estimates for all full-time employees. The AKM effects are estimated separately for the periods 1985–1992, 1993–1999, 2000–2006, 2007–2013, and 2014–2021. To ensure time-consistent estimates across these period boundaries, we demean the AKM effects at the year level.[6] Since these effects form the basis of our spatial sorting measures, we exclude all observations with missing worker or establishment fixed effects. We further restrict our sample to individuals earning a daily wage of at least €10 (CPI-adjusted to the base year 2015) to exclude implausibly low reported wages. Our final sample spans 1985–2021, covers five distinct AKM estimation periods, and comprises approximately 11.2 million

[4] The information on daily wages in the SIAB data is top-censored at the social security contribution ceiling. Censored observations were imputed following Stüber et al. (2023), controlling for gender, part-time status, age, tenure, and skill groups. We adapted the code from Stüber et al. (2023) to accommodate the then most recent SIAB version 7521.

[5] After German reunification in 1990, the former communist East Germany underwent a radical transition from a planned economy to a market-based system. These transformation processes were not fully completed by the end of the century and thus potentially obscure any changes in spatial inequality within the region. Additionally, the significant wage disparities between East and West Germany would complicate the assessment of the colocation trends in the much larger West German economy when pooling both parts of the country.

[6] In CHK – as in other implementations – AKM estimation is performed such that the levels of employer effects (and thus also worker effects) are identified relative to an arbitrary reference employer. This reference is fixed within, but not across, AKM estimation periods. As a consequence, the absolute levels of the estimated AKM effects can shift arbitrarily between estimation periods. To ensure comparability over time, we neutralize these shifts by demeaning AKM effects within each year using national averages.

observations (roughly 300,000 per year). Table 1, Panel A summarizes key worker-level statistics.

To investigate colocation and spatial inequality, we aggregate individual SIAB records to the county level, using each worker's place of employment. County-averaged establishment effects are based on employment weighted establishment effects (Card et al. 2025). For each county-year, we compute the average establishment and worker AKM effects (as well as the average of certain other worker or employer characteristics). Thus, the county serves as our unit of observation. We do not weight counties by size, as doing so would diminish the relevance of rural areas, which play a central role in public debates on spatial inequality and lagging regions.

We merge the SIAB-derived county aggregates with two external sources. First, we integrate county-level measures of export and import exposure to China and Eastern Europe from Dauth et al. (2014),[7] which quantify regional trade shocks. Second, we incorporate data on regional characteristics from the Federal Office for Building and Regional Planning (BBSR), including indicators of rurality, total population, and the annual unemployment rate.

Collectively, the county-level aggregates from the SIAB and the two external sources form a panel dataset covering the period 1985–2021. In Table 1, Panel B, we present all county-level variables used in the analysis. As our empirical focus will be on the period from 1998 to 2008, the table reports the corresponding changes over that particular decade.

3. The Anatomy of Rising Colocation

3.1. Wage Inequality

Beginning in the late 1990s until the late 2000s, Germany experienced a sharp increase in wage inequality. Dustmann et al. (2014) document this trend until 2008. CHK further demonstrate that important drivers behind the increase in wage inequality are growing disparities in workers' wage premia (worker effects) and the rise in assortative matching (covariance of worker and establishment effects). Table 2 extends the key findings from CHK for our sample through 2021. The table shows that the variance in log wages increased significantly from 0.198 to 0.298 between periods 1 (i.e. 1985-1992) and 4 (i.e. 2007-2013). This upward trend is partially reversed by the decline to 0.269 in period 5 (i.e. 2014-2021).[8] Focusing on the major increase

[7] Dauth et al. (2014) derive county-level trade exposure measures using the United Nations Comtrade database. They first calculate national industry–specific export and import flows and construct each county's exposure by weighting these flows according to its local industry employment shares.

[8] One potential explanation for the decrease in inequality is the introduction of the national minimum wage in 2015 (Bossler and Schank 2023).

between Period 2 and Period 4, we find that the variance of log wages rose by a remarkable 49%.

The variance of log wages (y_i) can be decomposed into the variances of the following components contained in CHK's AKM decomposition: worker effects (α_i), establishment effects ($\psi_{J(i,t)}$), life cycle effects ($x_{it}'\beta$) and an error term (r_{it}), respectively, as described in Equation (1). Most importantly, worker effects capture worker productivity and may change due to an increase in worker skills or the returns to worker skills whereas establishment effects capture, for instance, a pass-through of productivity to wages, i.e. rent-sharing (Card et al. 2018, Hirsch and Mueller 2020). While estimates for the worker and establishment fixed effects from CHK are provided by the IAB RDC, life cycle effects and the residual term are not provided and, as we do not have access to the full IAB population data, we can not compute them ourselves.

$$(1) \qquad Var(y_i) = \underbrace{Var(\alpha_i) + Var(\psi_{J(i,t)}) + 2Cov(\alpha_i, \psi_{J(i,t)})}_{observed\ by\ us}$$
$$+ \underbrace{Var(x_{it}'\beta) + 2Cov(\alpha_i, x_{it}'\beta) + 2Cov(\psi_{J(i,t)}, x_{it}'\beta) + Var(r_{it})}_{unobserved\ by\ us}$$

Based on the worker and person effects, we confirm the main findings by CHK and show that the variance of worker effects (43%) and assortative matching of workers and establishments (25%) are primarily responsible for the increase of wage inequality. The increase in establishment wage premia (establishment effect) explains another 15% in our data. Depending on the period, we can explain up to 90% of the variance of log wages by the worker and establishment effects and their covariance alone.

We contrast overall worker-level inequality with spatial inequality between regions. To this end, we estimate the average wage for all 324 West German counties (c) and calculate the variance between them. This between-county variance ($\bar{y}_c$) serves as our measure of spatial inequality. In addition to the between-county variance of average log wages, we also estimate the respective average county-level worker ($\bar{\alpha}_c$) and establishment effects ($\bar{\psi}_c$) as described in Section 2. This approach allows us to decompose spatial inequality into the components shown in Equation (2). The between-county variance of log wages thus consists of the variance of average county-level worker effects, the variance of average county-level establishment effects, and the county-level covariance between average worker- and establishment effects, and terms that are unobserved to us. The covariance between average worker- and establishment effects measures between-county sorting and we refer to this as colocation.[9]

$$(2) \qquad Var(\bar{y}_c) = \underbrace{Var(\bar{\alpha}_c) + Var(\bar{\psi}_c) + 2Cov(\bar{\alpha}_c, \bar{\psi}_c)}_{observed\ by\ us}$$
$$+ \underbrace{Var\left(\overline{x_c'\beta}\right) + 2Cov\left(\bar{\alpha}_c, \overline{x_c'\beta}\right) + 2Cov\left(\bar{\psi}_c, \overline{x_c'\beta}\right) + Var(\bar{r}_c)}_{unobserved\ by\ us}$$

Table 3 shows that spatial inequality rose significantly from 0.0088 in period 2 to 0.0138 in period 4 - a 57% increase, compared to a 49% rise in overall wage inequality. The prior and subsequent declines were small. The two main drivers of rising spatial inequality mirror those driving overall log wage inequality: the increase in the variance of average county-level worker effects (48%) and the increase in colocation (40%) (Panel B, Table 3). In contrast, changes in the variance of average county-level establishment effects (7%) play only a minor role.[10] Compared to its 25% share in overall inequality (Table 2), sorting thus contributes significantly more to the rise in spatial inequality. The rising variance of worker effects is a major factor in both cases whereas the variance components unobserved to us play only a minor role.[11]

3.2. Colocation

Figure 1 shows the evolution of spatial log wage inequality (between-county variance in log wages) and of colocation between 1985 and 2021 for Western Germany. Spatial wage inequality slightly declined in the early 1990s but then rose sharply between the late 1990s and around 2008. After 2008, inequality declined modestly. Figure 1 shows a slight increase in colocation between 1985 and 1998 followed by a sharp increase until the 'Great Recession' of 2008 and a slight decline thereafter, thereby closely mimicking the evolution of spatial inequality. The most important result of Figure 1 is thus that the increase in colocation takes place during a well-defined episode with little change before and after. Results at the level of labor market regions (instead of counties) show the same pattern (cf. Appendix Figure B.1).

[9] Equation 2 also clarifies why assessing changes in the covariance, rather than in the correlation, is appropriate for understanding changes in spatial inequality.
[10] We alternatively use labor market regions (cf. Appendix B) instead of counties to test whether our results depend on the level of aggregation. Results corresponding to Table 3 are reported in Appendix Table B.1. Although spatial inequality is generally lower at this higher level of aggregation, the patterns and their timing closely resemble those at the county level.
[11] By adding up the within-period contributions of the observed variance components in Panel B of Table 3 one can verify that the part of equation (2) that is unobserved to us, i.e. the total variance of average life-cycle effects ($\overline{x_c'\beta}$) along with its correlation with worker and establishment effects as well as the variance of the average error term ($\bar{r}_c$), account for no more than 6% of the total variation in average county wage variation from period 2 onwards. In period 1, they can explain 14%.

Changes in colocation can arise both within and between AKM estimation periods. Within a given AKM period, variation mainly reflects worker mobility across counties, labor force entries and exits, or changes in employer size (as employer effects are size-weighted). Between AKM periods, colocation can also shift due to the re-estimation of the AKM model. As our within-year demeaning of AKM effects accounts for cross-period changes that are simply due to the specific AKM estimation procedure applied (cf. section 2), such between-period changes may capture structural shifts in the returns to skills or in employer pay components rather than short-run mobility or firm dynamics. Figure 1 shows that changes in colocation are visible between AKM periods and this already hints that mobility and dynamics may not be the sole forces behind the rise in colocation — a point we will return to in more detail below.

The two binned scatter plots in Figure 2 illustrate how the link between worker and establishment effects across West German counties strengthened over time. Spatial sorting was already present in 1998 (slope: 0.654) but intensified markedly over the following decade (slope: 1.027), an increase of about 57%. The 2008 results imply that workers in regions with a 10 log-point higher establishment effect also have, on average, 10 log-points higher worker effects. The figure underscores a growing divide between counties with low average worker and establishment effects and those with high values for both, reflecting rising spatial polarization.[12]

Mechanically, this increase in colocation could occur through the following mechanisms:

A: Changes in establishments' pay policies across regions: Employers´ pay policies may be adjusted at constant worker effects. For example, regionally clustered negative demand shocks may force high-paying employers with low-wage employees to reduce their employer pay premium.[13]

B: Changes in incumbent workers´ wage premia across regions: Growth in the returns to incumbent worker skills may differ based on the employer´s initial pay policy. High-paying employers may operate in different markets than low-paying employers, being affected differently by developments such as trade integration. This may, for example, lead to higher skill demand by high-wage employers further driving up wages of their high-skill workers reinforcing pre-existing colocation.

[12] Again, patterns at the level of labor market regions are very similar showing a 49% increase between the two periods (cf. Appendix Figure B.2)

[13] In fact, industry-specific shocks in combination with regional industry clustering contributed to rising colocation in the U.S. (Diamond 2016).

C: Increased worker mobility: Mobility includes both the migration of incumbent workers and labor market entries and exits. Colocation increases, for instance, if the aforementioned changes in labor demand trigger migration of incumbent high-wage workers out of low-wage counties whereas rising house prices may drive low-wage workers out of high-wage counties (Diamond 2016). Similarly, an increasing inflow of young, well-educated labor market entrants into high-wage counties (Moretti 2012) or the labor market exit - whether temporary or permanent - of low-wage workers from high-wage counties would increase colocation.

Thus, the rise in colocation could follow distinct patterns, each potentially driven by different economic phenomena. From a welfare perspective, Scenario A and B have the advantage that they do not involve across-region relocation costs for workers, which, however, may come at the cost of foregoing the benefits strong agglomeration effects may have on aggregate productivity and beyond. In contrast, Scenario C entails migration of workers across regions, involving relocation costs and profound changes to the workforce composition of local labor markets and communities. In the following, we will revisit which of the three scenarios contributes most to the rise in colocation.

We begin with a suggestive, graphical analysis before turning to the fully-fledged covariance decomposition. Figure 3 presents four county-level binned scatter plots. The top-left Panel A illustrates that between 1998 and 2008, average wages in West Germany increased more in counties that already had higher worker effects in 1998. Similarly, the top-right Panel B shows that wages rose most in West German counties where establishment effects were higher in 1998, indicating that counties with the best-paying (and arguably most productive) establishments experienced the strongest wage growth. The slope in Panel B (0.327) is considerably higher (+59%) than that of Panel A (0.206), which implies that colocation is mainly driven by counties with the best paying employers, which is a key result to which we will get back to frequently in this paper.

A key question then arises: Is this wage growth driven by increases in establishment effects or worker effects? The bottom-left panel of Figure 3 demonstrates that the evolution of establishment effects is slightly negatively related to their initial levels (slope -0.077). This convergence in establishment effects suggest that Scenario A is not the primary explanation for the rise in colocation – in fact, it *ceteris paribus* reduces colocation. Finally, the bottom-right panel shows a strong increase in average worker effects in counties initially hosting the best-paying employers (slope 0.476). Thus, the rise in colocation is either the result of intra-county changes of incumbent worker´s pay premia (Scenario B) or of worker mobility (Scenario C).[14]

3.2.1. Shift-share and covariance decomposition methodologies

To thoroughly examine the origins of the increased colocation, we apply a formal covariance decomposition. Using the properties of the covariance operator, we can write

$$\Delta \text{Cov}(\overline{\alpha}_c, \overline{\psi}_c) = \text{Cov}(\overline{\alpha}_c^{1998}, \Delta\overline{\psi}_c) + \text{Cov}(\Delta\overline{\alpha}_c, \overline{\psi}_c^{1998}) + \text{Cov}(\Delta\overline{\alpha}_c, \Delta\overline{\psi}_c) \quad (3)$$

where Δ denotes the change between 1998 and 2008. The results of this basic decomposition are shown in Panel B of Table 4 and add a quantification to the graphical results in Figure 3: the entire increase in the covariance between 1998 and 2008 is attributable to changing worker effects whereas changes in the establishment effect play no role.[15]

As is evident from these results, a further decomposition of the worker effect contribution to the covariance into a component from stayers (Scenario B) versus mobility flows (Scenario C) is of particular interest. To this end, we first decompose the change in the average county-level worker effect into a stayer component and four mobility components, as outlined in Appendix A.[16] The result of this shift-share decomposition reads as follows:

$$\begin{aligned} \Delta\overline{\alpha}_c = \overline{\alpha}_C^{2008} - \overline{\alpha}_C^{1998} = \left(\overline{\alpha}_S^{2008} - \overline{\alpha}_S^{1998}\right) + \\ \frac{N_{IE}}{N_{2008}}\left(\overline{\alpha}_{IE}^{2008} - \overline{\alpha}_S^{2008}\right) + \frac{N_{IM}}{N_{2008}}\left(\overline{\alpha}_{IM}^{2008} - \overline{\alpha}_S^{2008}\right) \\ - \frac{N_{OX}}{N_{1998}}\left(\overline{\alpha}_{OX}^{1998} - \overline{\alpha}_S^{1998}\right) - \frac{N_{OM}}{N_{1998}}\left(\overline{\alpha}_{OM}^{1998} - \overline{\alpha}_S^{1998}\right) \end{aligned} \quad (4)$$

where S denotes stayers, individuals working in the same county in both 1998 and 2008, IE denotes in-movers who are entrants (or re-entrants) to the labor market (working in county c in 2008 but are not in the data in 1998), and IM denotes in-movers (working in county c in 2008 and in another county in 1998). Correspondingly, OX denotes those leaving the labor market (permanently or temporary) and OM out-movers (working in county c in 1998 and in another county in 2008). $N_{IE}, N_{IM}, N_{OX}, N_{OM}$ measure the number of workers in the respective groups,

[14] Appendix Figure B.3 illustrates that the county-level patterns shown in all panels of Figure 3 carry over to the level of labor market regions.
[15] Appendix Table B.2 show very similar results at the level of labor market regions.
[16] Remember that we normalize the average AKM worker (and firm) effects to be zero within each year to ensure that changes in worker effects across AKM estimation periods reflect changes in worker productivity rather than changes in some reference category chosen for the AKM estimation. For details see Section 2.

whereas N_{2008} and N_{1998} measure the total number of workers in the target and base year, respectively.

The first term in equation (4) captures the contribution of changes in the AKM worker effects of stayers to the overall change in counties' worker effects, which we refer to as the 'stayer effect'. The second and third term measure the contribution of quality differences between the two groups of in-movers (*IE* and *IM*) and stayers, respectively, weighted by their share in county employment. Similarly, the last two terms reflect the contribution of the two groups of out-movers, weighting the difference between the quality of out-movers (*OX* and *OM*) and stayers, respectively, with their shares.

Plugging the shift share terms into equation (3) yields a decomposition of the covariance into eleven components of which we show the most relevant here.[17]

(5)
$$\begin{aligned}
\Delta\mathrm{Cov}(\overline{\alpha}_c, \overline{\psi}_c) &= \mathrm{Cov}\left(\overline{\alpha}_c^{1998}, \Delta\overline{\psi}_c\right) \\
&+\mathrm{Cov}\left(\overline{\alpha}_S^{2008} - \overline{\alpha}_S^{1998}, \overline{\psi}_c^{1998}\right) \\
&+\mathrm{Cov}\left(\frac{N_{IE}}{N_{2008}}\left(\overline{\alpha}_{IE}^{2008} - \overline{\alpha}_S^{2008}\right), \overline{\psi}_c^{1998}\right) \\
&+\mathrm{Cov}\left(\frac{N_{IM}}{N_{2008}}\left(\overline{\alpha}_{IM}^{2008} - \overline{\alpha}_S^{2008}\right), \overline{\psi}_c^{1998}\right) \\
&-\mathrm{Cov}\left(\frac{N_{OX}}{N_{1998}}\left(\overline{\alpha}_{OX}^{1998} - \overline{\alpha}_S^{1998}\right), \overline{\psi}_c^{1998}\right) \\
&-\mathrm{Cov}\left(\frac{N_{OM}}{N_{1998}}\left(\overline{\alpha}_{OM}^{1998} - \overline{\alpha}_S^{1998}\right), \overline{\psi}_c^{1998}\right) \\
&+ \text{crossterms}
\end{aligned}$$

3.2.2. Results shift share analysis

The results of the shift-share decomposition are shown in Panel C of Table 4 and we focus on the period 1998-2008 in the following. Stayers contribute positively to the change in counties' average worker effects. This is expected, as workers gain experience over time or may get promoted etc., which is reflected in rising worker effects. On average, county-level worker effects for stayers rise by 2.96 (worker effects have been multiplied by 100 to ease exposition), whereas overall worker effects decline by 1.63. As it turns out that the cross-county mover contributions (IM, OM) are tiny compared to the entry and exit contributions (IE, OX),[18] we

[17] For any covariance it holds that $cov(A + B, C) = cov(A, C) + cov(B, C)$. We summarize the cross terms between the change in the firm effect and the change in the shift-share components into one composite covariance term. The full set of covariance terms can be found in Appendix A.
[18] Results available upon request.

report a composite in-mover and out-mover term, respectively. The sum of all four mobility components is strongly negative (-4.59). In-movers are typically inexperienced or join from non-employment and thus add low worker effects to the county average. This is reflected in a strong negative contribution (-6.25). Out-movers are either highly experienced workers (typically having high worker effects) entering retirement or those entering unemployment. On net, their exit raises average worker effects by 1.66, implying that the worker effects of out-movers were below that of stayers (but above that of in-movers).

More important for colocation than the gross changes are differences in shift-share components across counties. To understand the contributions of stayers versus mobility, we relate these components to initial employer effects at the county level. From Figure 2 we know that colocation intensified, and from Figure 3 that changes in the AKM worker effect are strongly positively correlated with initial employer effects. Figure 4 strikingly shows that the stayer component rises almost monotonically with initial employer effects, implying that returns to incumbent workers' skills increased with initial employer effects. Appendix Table A.1 provides descriptive evidence on group composition and illustrates that stayers in high-wage counties had higher education levels than their low-wage county counterparts and are more likely to work in manufacturing.[19]

Figure 4 shows that the negative labor market entry (IE) component remains fairly constant across the distribution of initial employer effects. Importantly, this does not imply that entrants are of similar quality across the initial county-level establishment effect distribution, since the in-mobility component compares the quality of a county's entrants to that of its stayers, weighted by the share of entrants in total employment. This share is quite stable across the 12 bins shown in Figure 4. Because the in-mobility effect is measured relative to the quality of stayers – who were already of much higher quality in high-wage counties in the base year (cf. Figure 2) – constant shares imply that (i) high-wage counties attract higher-skilled entrants and that (ii) this process roughly preserves the skill distance between counties. Appendix Table A.1, for instance, shows that the share of college graduates among labor market entrants is much higher in the top counties (20.2%) than in the low-paying counties (9.3%) and that average worker effects are also much higher in the top counties (-0.044 versus -0.201). The labor market exit component is smaller and positive, with a larger effect in low-wage counties, suggesting that the least productive workers are more likely to leave those counties, which stabilizes

[19] Since Appendix Table A.1 offers insights that extend beyond what can be covered in the main text, Appendix A.1 includes a short section that summarizes and highlights these additional findings.

average worker effects there.[20] Overall, the shift–share results indicate that the link between changes in worker effects and initial employer effects (Figure 3) is mainly driven by differential increases in returns to incumbent workers pay premia (stayer effect, Scenario B) and is largely unaffected by mobility flows (Scenario C).

3.2.3. Results of the decomposition of the change in colocation

The results of the formal decomposition of the 1998 – 2008 increase in colocation are presented in Panel D of Table 4. First, the contribution of establishment pay policies reduced colocation by about 6% implying that - with worker effects held constant - colocation would have declined slightly. The main result is that the stayer effect is dominant: had there been no mobility between 1998 and 2008 – i.e. no workers switching counties and no entry to and exit from employment – colocation would have risen by 0.167 instead of the observed 0.113 (+48%). Mobility reduced colocation by 0.048 (-42%) of which 34 percentage points are attributable to out-mobility and 14 percentage points to in-mobility.[21]

Figure 5 plots the covariance contributions of employer pay policies, stayers, in-mobility, and out-mobility across the distribution of initial employer effects. A clear polarization is visible: the strongest positive contributions to colocation occur at the extremes of the initial employer effects distribution. The decomposition highlights that these positive contributions are almost exclusively driven by the stayer component. Recalling the results in Figure 3 and Figure 4, we can infer from Figure 5 that overall colocation rises because low-paying counties contribute through declining worker effects of stayers – an effect partly offset by out-mobility – while high-paying counties contribute through sharply rising worker effects of stayers, counteracted by mobility flows (and to a lesser extent by pay policies and cross terms). Out-mobility reduced the rise in colocation by lifting worker effects in low-wage counties and depressing those at the high-wage counties. The contribution of employer pay policies plays no significant role across the entire distribution.

Overall, this quantification of the relative importance of mobility versus heterogeneous growth in worker pay premia across counties strongly confirms our previous findings. We conclude that most of the increase in colocation arises from widening pay-premium differentials among stayers, which amplify pre-existing spatial sorting between establishments and workers. Sorting

[20] Again, out-mobility shares (OM+OX) are highly similar across the 12 bins in Figure 4.

[21] Mobility contributions are mainly determined by IE and OX whereas IM and OM are unimportant. Results available upon request.

via mobility flows – mostly through entry into and exit from employment – counteracts the stayer effect and reduces colocation.[22]

4. Explaining the rise in colocation: International Trade and Colocation

Before turning to any specific mechanism, the empirical results above discipline the set of plausible explanations. The rise in colocation was not primarily driven by changes in establishment wage premia, nor by the relocation of workers across space. Instead, it reflected rising worker pay premia among incumbent workers in counties that were already home to many high-wage workers and high-wage establishments.

A successful explanation for the rise in colocation therefore needs to satisfy a relatively demanding set of conditions. It should (i) reflect a major economic change between 1998, or slightly before, and 2008; (ii) affect worker effects; (iii) leave establishment effects largely unaffected; and (iv) operate mainly in initially high-paying counties. In a country with limited spatial mobility of incumbent workers, a suitable candidate explanation will thus affect colocation through the worker effects of stayers in high-wage counties.

Several broad economic forces could, in principle, have contributed to the rise in colocation. For instance, the major expansion in tertiary education in Germany could have increased colocation by attracting more talent from rural areas to agglomerations with universities. However, the rise in tertiary education enrollment happened well after the seminal increase in colocation (cf. Figure A.1), and it could not explain that colocation reflected rising worker pay premia among incumbent workers. The decline in collective bargaining coverage could in principle have driven colocation, but – as opposed to our results – it should have operated through changes in employer pay premia rather than worker premia (see Hirsch and Mueller 2020). Domestic outsourcing (Goldschmidt and Schmieder 2017), describing the outsourcing of low-wage activities to low-paying service providers, drives colocation at the worker-firm level, i.e. assortative matching, but should operate mostly within rather than across counties.

[22] We show below that the type of trade exposure can account for why effects are concentrated among stayers. We do not, however, seek to explain why German workers exhibit lower geographic mobility than, for example, U.S. workers. A number of institutional and structural factors are likely to matter. In particular, housing market characteristics are salient: renting, rather than home ownership, is far more common in Germany, and strict rent regulations imply that long-term tenants typically pay considerably lower rents than newcomers. This wedge between incumbent and entrant rents in booming regions reduces both the incentive for long-term tenants to move out and the ability of potential in-migrants to move in. For short summary see e.g. https://www.brookings.edu/articles/Germany-rental-housing-markets/. Recently, Glitz et al. (2025) find evidence for large gaps between incumbent rents and market rents that limit mobility. They argue that about half of this gap is due to regulation.

Immigration represents another potential contemporaneous force, but the period 1998–2008 was not characterized by a large new immigration wave. What is more, immigration is unlikely to explain our findings, as it does not fit our core result that pay premia increased among stayers rather than via labor market entrants.

For reasons detailed below, we focus on rising international trade as one theoretically plausible and, given the large increases in trade exposure, potentially quantitatively important driver. Our focus on trade integration does not rule out other explanations or combinations of them.

4.1. Background and Hypotheses

This section investigates in a regression framework whether and how a very important economic shift – namely the rise of international trade between 1998 and 2008 – can explain colocation and the aforementioned mechanisms driving it. We look at trade for two reasons. First, the period from 1998 to 2008 was marked by rapid growth in international trade, in particular growth in German exports. Second, as we explain below, trade theory predicts that export growth should reinforce pre-existing colocation by raising worker effects in high-wage counties. Specifically, we empirically examine (1) whether trade exposure increased most strongly in high-paying counties, (2) how trade exposure affected worker effects across counties, and (3) how it influenced each county's contribution to rising colocation.

Dauth et al. (2014) document in their important work how Germany faced both the rise of China and the entry of Eastern Europe[23] into the global market following the fall of the 'Iron Curtain'. West Germany benefited from trade in terms of employment, largely through significantly increasing its exports to these new markets. In stark contrast to the U.S. experience, trade with Eastern Europe – which is geographically close – proved even more consequential for Germany than trade with China. Appendix Table C.1 shows that exports to (and imports from) both regions rose from €68 billion (€70) billion in 1998 to €198 billion (€191) billion in 2008. Importantly, exports to Eastern Europe are (depending on the year) between four to eight times larger than exports to China. About 78% of the total 1998 - 2008 export growth to the two regions is attributable to Eastern Europe. In the base year, imports from Eastern Europe were about three to four times larger than imports from China and remained about twice as large in the target year. Import growth was roughly equally distributed between the two regions.

[23] Eastern Europe includes Russia and the other former Soviet Union member states as well as all other Eastern European countries except most of former Yugoslavia due to the war (only Slovenia is included).

Economic theory predicts that increased *export* opportunities will exacerbate pre-existing colocation. First, the most productive firms self-select into export markets (Melitz 2003), a process that concentrates export activity among ex ante highly productive regions. Figure 6 indeed shows a very tight positive link between counties' initial establishment effects, serving as a proxy for productivity, and subsequent export growth. Hence, counties where high-paying firms clustered increased their exports the most. Building on the insights in Melitz (2003), Helpman et al. (2010) show that, after an economy opens to trade, exporting firms' rising revenues strengthens their incentives to hire and retain high-ability workers.[24] Sampson (2014) also combines Melitz (2003) with production complementarity between productive firms and high-skilled workers and concludes that trade will raise wages of high-skilled workers. Schank et al. (2007) show that German employers with a higher export share in sales indeed pay higher wages and Dauth et al. (2021) show empirically that exporting benefits the earnings of high-skilled workers in Germany most. The logic in Helpman et al. (2010) and Sampson (2014) and the existing empirical evidence imply that average worker effects should increase in ex ante high-paying places, which thus reinforces pre-existing colocation and triggers precisely the colocation mechanisms that we presented in Section 3.

Further supporting those predictions, German exports are skill-intensive, comprising specialized machinery and high-quality vehicles whose production involves substantial R&D and relies on highly trained engineers, technicians, and workers (see our analysis on trade composition in Appendix C). It is therefore plausible that (i) these exporters had above average productivity before the rapid trade integration, (ii) already employed high-skilled workers, and (iii) that exports increased demand for high-skilled labor further. We will demonstrate in the following that our empirical results confirm all those theoretical predictions and that trade integration is also quantitatively important.

Basic theory predicts declining labor demand in import-shocked counties and, thus, implications for colocation depend on whether initially high- or low- paying counties are affected more. Unlike in the case of exports, there is no inherent mechanism ensuring that import shocks disproportionately affect regions based on the magnitude of pre-existing establishment effects. Empirically, Dauth et al. (2021) report that workers in high-paying establishments were primarily affected. In line with this finding, Figure 6 shows a positive association between initial establishment effects and subsequent import growth, which suggests

[24] Although Helpman et al. (2010) do not specifically discuss AKM-style worker- and establishment effects they explicitly allow the interpretation of ability as being unobserved and not specific to a match and state that inequality has a worker and a firm component under this interpretation (Helpman et al. 2010:1242).

that import growth should have weakened colocation by reducing worker effects in *ex ante* high-paying places.

We estimate county-level regressions of changes in average worker effects on changes in import and export exposure to assess the impact of trade on worker effects and colocation. The regression framework is designed to follow Dauth et al. (2014) as closely as possible to facilitate comparisons.[25] Local industry composition is combined with industry specific trade shocks at the national level via a shift share approach and this yields regional trade exposure in Euro per manufacturing worker. We control for initial conditions by including measures for rurality, population, worker age, unemployment rate, college share, and manufacturing employment share.

The resulting first-differenced regressions are estimated using an instrumental variable approach, where trade exposure is instrumented with international trade patterns to deal with endogeneity concerns (Autor et al. 2013). We again follow Dauth et al. (2014) and instrument trade exposure of German regions to China and Eastern Europe with the corresponding trade exposures of the following countries: Australia, Canada, Japan, Norway, New Zealand, Sweden, Singapore, and the United Kingdom.[26]

Similarly, we regress each county's contribution to the increase in colocation on changes in trade exposure. For a given period, a county's contribution is defined as its deviation from the national averages in worker and establishment effects, multiplied together and scaled by the inverse of the number of counties. The change in a county's contribution is then the difference between its contribution in the target year and the base year. By construction, summing up these county-level contributions over the 324 counties reproduces the aggregate change in colocation. Hence, we will report estimated county-level coefficients multiplied with 324 such that coefficients directly reproduce the change in colocation for a 1,000 Euro increase in trade exposure.[27] More details are given in Appendix C.

4.2. Export Growth

Export growth and worker effects

[25] As done throughout Section 4 we further multiply the coefficient by 100 for ease of interpretation.
[26] Subsequent research has refined the trade-exposure estimations of Autor et al. (2013) and Dauth et al. (2014), for example by introducing formal diagnostics of the Bartik instruments (Borusyak et al. 2022). Borusyak et al. (2022) find little evidence for failure of the identification strategy in Autor et al. (2013).
[27] As done throughout Section 4 we further multiply the coefficient by 100 for ease of interpretation.

Table 5 presents instrumental variable regression results for the effect of trade with Eastern Europe and China on changes in the average worker effect across counties. The coefficients are multiplied by 100 for ease of interpretation. Our preferred specification with full controls in column (3) shows a significant positive impact of export exposure on county-level average worker effects. An average increase in export exposure of €1,000 per manufacturing worker is associated with an increase in worker pay premia of 0.990. To assess the quantitative importance of this estimate, we conduct a simple back-of-the-envelope ceteris paribus exercise and multiply total 1998-2008 county-averaged changes in our trade exposure with our regressor of interest. As export exposure increased by €5,460 per manufacturing worker on average across counties (cf. Appendix Table C.1), the coefficient of 0.990 implies a total change in worker pay premia of 5.4, i.e. 5.4% wage growth. This estimated effect exceeds the mean change in average county-level worker effects (–1.63 with a standard deviation of 3.8; again these numbers have been multiplied with 100) and, thus, in the absence of this export shock, worker pay premia would have decreased even more.

Exports to Eastern Europe grew much stronger than exports to China with average per capita €4,250 as opposed to €1,209. Maintaining the specification in column (3) of Table 5, Table 6 demonstrates that the marginal effects per €1,000 change in export volume are similarly strong for both Eastern Europe and China (though much more precisely estimated for Eastern Europe). Since export growth with Eastern Europe was much larger than with China we conclude that the vast majority of export effects are attributable to the opening of Eastern European markets. Table 6 further shows that export growth from Eastern Europe had the strongest impact on worker effects in the (highly shocked) ex ante high-paying counties again underlining that the export channel drives our results. Finally, the table confirms that – as predicted by the theoretical frameworks in Helpman et al. (2010) and Sampson (2014) – the effects of exports are concentrated in the upper terciles of the county-level distribution of 1998 worker effects.[28] Dauth et al. (2021) show that skilled workers in export exposed industries (not locations) see the highest earnings increase.

We have established so far that (i) colocation existed already before the sharp rise in export growth, (ii) export growth and the marginal effects of export growth were concentrated in regions that were already high-paying, and (iii) it indeed increased worker effects. We therefore expect export growth to increase colocation. Furthermore, results in Appendix Table C.2 show

[28] We rerun the regressions, replacing the dependent variable (average county-level worker effects) with average county-level worker effects in terciles of the county-level worker effects distribution. Thus, we estimate the effect of trade on the average worker effect in the, say, third tercile of the county-level wage premia distribution.

that exports particularly affected worker effects of *stayers*, which – as described in the previous sections – is precisely the group driving most of the rise in colocation. Appendix Table C.3 confirms that export effects on stayers happened in ex ante high-paying counties, only.

Export growth and colocation

Table 7 reports the results from estimating the effect of export growth on the change in each county's covariance contribution, pooling Eastern Europe and China. As expected, export growth increased colocation. The pooled coefficient implies that the county-average total change in exports of €5,460 per manufacturing worker (cf. Appendix Table C.1) raised colocation, ceteris paribus, by 0.224 (i.e. 5,460/1,000*0.041). This is about twice the observed increase in colocation of 0.113 (see Table 4).

While we have established that export growth fostered colocation by rising worker effects in ex ante high-paying counties, our data allows us to scrutinize the link between exports and colocation further. Table 8 shows the effect of export growth split by destination country. The marginal effects on colocation are large and statistically significant for exports to Eastern Europe (0.152). By contrast, exports to China are statistically insignificant and negative (–0.109), highlighting that exporting to Eastern Europe – but not to China – was decisive for the rise in colocation. Again, trade exposure had an impact on the covariance contributions of ex ante high-paying counties, only.[29]

4.3. Import Growth

Import growth and worker effects

Our summary of the effects of import growth follows the same ordering as that of export growth. Column (3) of Table 5 shows the expected negative impact of import exposure on worker effects of 0.340 per €1,000 of import growth per manufacturing worker, which is notably smaller (in absolute terms) than the effect of export growth. Counties experienced an average import shock of €4,216 per capita which implies a (ceteris paribus) change in worker pay premia of -1.4, i.e. 1.4% wage decline. This estimated effect is similar to the mean change in average

[29] For completeness, we show in Appendix Table C.4 that export growth had a negative impact on establishment pay premia that is, however, much smaller than the effect on worker effects and not precisely estimated. As export growth was concentrated in counties with high establishment effects, the negative effect on the establishment effect slightly muted the overall positive impact of exports on colocation.

county-level worker effects (–1.63 with a standard deviation of 3.8) implying that import shocks can almost fully explain the observed reduction in worker effects.

Maintaining the specification in column (3) of Table 5, Table 6 shows that the marginal effects per €1,000 change in import volume on worker effects are strongly negative for Eastern Europe (-1.80) and negative but close to zero for China (-0.26) Since import growth from Eastern Europe and China was of similar magnitude (Appendix Table C.1), this difference in the marginal effects implies that the impact of imports from Eastern Europe – as in the case of exports – was much larger than that of China. Table 6 confirms that import growth did only affect worker effects of middle and highly paid workers in ex ante high-paying counties. This is a notable difference to findings for the U.S. where negative wage effects of imports (not effects on AKM worker effects) tended to be concentrated among low and middle paid workers (Autor et al. 2014).[30]

Import growth and colocation

Given pre-existing colocation and the fact that both import growth and its negative marginal effects on worker wage premia are concentrated in ex ante high-paying regions, we expect import growth to dampen the rise in colocation. The results in Column (3) of Table 7 show a negative but statistically insignificant effect of imports on colocation of -0.015. The coefficient implies that the county-average total change in exports of €4,216 per manufacturing worker (cf. Appendix Table C.1) reduced colocation, ceteris paribus, by 0.063 (i.e. 4,216/1,000*0.015). This is about half the observed increase in colocation of 0.113 (see Table 4).

Table 8 provides the corresponding results split by destination country. It shows a negative and statistically significant for Eastern Europe (-0.155) and a smaller, imprecisely estimated negative effect of Chinese imports (-0.027). As in the case of export growth, import growth only affects the covariance contributions of ex ante high-paying counties.[31]

[30] The presence of rigid labor market institutions including strong employment protections and downward rigid (union) wages in Germany complicates theoretical predictions about import effects along the worker-effects distribution. A first likely explanation for the difference to the U.S. results is the aforementioned relatively high skill level and pay of manufacturing workers in Germany implying that negative demand effects also hit the medium and upper tercile. Secondly, employees and employers at the time made heavy use of pre-retirement and early retirement schemes for older workers (for an overview, see OECD 2005). As experience increases the worker effect, this policy could possibly explain a reduction in average wage premia in the middle and the highest worker effect terciles. Due to very strong employment protection for older workers, these retirement schemes should be particularly attractive for employers in times of declining labor demand.

[31] We show in Appendix Table C.4 that import growth had a small, negative but barely statistically significant impact on establishment pay premia thereby ceteris paribus muting the rise in colocation.

5. Conclusions

This study investigates the drivers of increasing spatial wage inequality between West German counties. Most of this increase happened between 1998 and 2008 and can be traced back to a growing covariance between worker and establishment fixed effects, called colocation. We show that changes in establishment pay premia do not contribute to rising colocation. Colocation was primarily driven by an increasingly unequal spatial distribution of worker effects. This pattern stems mainly from differential growth in worker pay premia among stayers, while labor mobility reduced colocation. Growth in worker pay premia was strongest for high-wage stayers in initially high-wage counties but negative for stayers in initially low-wage counties, thereby strongly reinforcing pre-existing colocation. The overall outcome is thus probably best described as 'rising colocation without relocation'. This empirical pattern substantially narrows the set of plausible explanations for rising colocation. Candidate mechanisms must account for rising worker effects among stayers in initially high-paying counties, while leaving establishment effects largely unaffected and without relying on worker relocation across space.

Turning to the economic forces at play, the relevant period was characterized by a tremendous rise in trade integration of the German economy, driven both by China's emergence as a global exporter and by the opening of Eastern Europe to trade. Economic theory predicts that increased export opportunities will exacerbate pre-existing colocation, a prediction reinforced by the skill-intensive nature of German exports. Our analysis shows that exports significantly raised county-level worker effects, whereas imports had the opposite effect, though to a smaller extent. Both the incidence of export and import shocks and the marginal effects on worker effects were concentrated in counties with ex ante high establishment effects. Thus, export growth boosted colocation, while import growth muted it and both effects were indeed most pronounced among stayers. Because export growth was stronger and had a larger absolute impact on worker effects, trade ultimately reinforced pre-existing colocation in Germany. Quantitatively, export growth – indeed, even net export growth alone – accounted for more than the entire rise in colocation. We therefore interpret trade integration as a central mechanism behind rising colocation, without claiming that it was the only economic force shaping regional wage inequality over this period.

Differences in trade patterns help explain why the mechanisms transporting colocation differ between Germany and the United States. In Germany, export growth in already high-paying regions raised skill demand and increased colocation without requiring spatial mobility of workers. In the United States, by contrast, structural labor-demand shifts – driven in part by import competition – induced high-wage workers to move toward high-wage locations (Diamond 2016) and to leave import-shocked regions (Autor et al. 2021).

The differing patterns of how colocation evolved in the two countries may have starkly differing implications for spatial cohesion and aggregate productivity. Our evidence implies that lagging regions in Germany retain their skill base to a larger extent than lagging regions in the U.S., which may reduce social conflict and ease future convergence in Germany. On the other hand, if worker skills and firm productivity are complements in production and agglomeration forces are important among high-skilled workers (Moretti 2012), the German economy may pay for lacking regional mobility via reduced aggregate productivity growth. We leave those questions for future research.

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Tables and Figures

Table 1: Summary statistics

Panel A: Worker Level (1985-2021)					
Variable	Obs	Mean	Std. dev.	Min	Max
Log wage	11179365	4.642	0.496	2.303	7.659
Worker effect	11179365	0	0.369	-4.031	3.050
Establishment effect	11179365	0	0.198	-3.352	2.724
Worker age	11179365	39.47	10.63	20	59
College share	11015106	13.97	34.66	0	100
Manufacturing share	11179365	34.11	47.41	0	100
Panel B: County Level (1998-2008)					
Variable	Obs	Mean	Std. dev.	Min	Max
Import exposure (Eastern Europe + China) in €1,000 per manufacturing worker	324	4.216	2.592	0.750	16.35
Export exposure (Eastern Europe + China) in €1,000 per manufacturing worker	324	5.460	2.948	0.336	21.09
Import exposure (Eastern Europe) in €1,000 per manufacturing worker	324	2.104	1.312	-0.392	9.550
Export exposure (Eastern Europe) in €1,000 per manufacturing worker	324	4.250	2.220	-0.188	15.62
Import exposure (China) in €1,000 per manufacturing worker	324	2.112	1.874	0.277	12.46
Export exposure (China) in €1,000 per manufacturing worker	324	1.209	0.829	0.170	5.839
Δ avg. county worker effect (x 100)	324	-1.633	3.758	-11.16	16.62
Δ avg. county establishment effect (x100)	324	0.358	2.397	-7.831	6.619
Covariance contribution (x 10,000)	324	0.035	0.084	-0.237	0.550
Rurality (percentage points)	324	25.88	28.79	0	100
Population (1998) in 10,000 inhabitants	324	19.95	17.09	3.575	170.0
Unemployment rate (1998) in %	324	8.970	2.809	4.040	19.33
Avg. age (1998) in years	324	38.42	0.845	35.46	40.22
College share (1998) in %	324	8.454	4.272	1.548	30.13
Manufacturing share (1998) in %	324	37.45	11.91	9.953	73.31

Note: Panel A: Worker and establishment effects are centered around their respective means. Panel B: Export and import exposure measure trade shocks from 1998–2008; changes in average county worker and establishment effects also refer to 1998–2008. Rurality is time-invariant and gives the share of a district's population living in municipalities with fewer than 150 inhabitants per km². Sample: SIAB data, full-time workers, West Germany.

Table 2: Worker-level log wage inequality

Panel A						
	Period 1 1985-1992	Period 2 1993-1999	Period 3 2000-2006	Period 4 2007-2013	Period 5 2014-2021	Change Period 2 to Period 4
Variance of log wages	0.198	0.200	0.259	0.298	0.269	0.098
Variance of worker effects	0.108	0.117	0.140	0.159	0.163	0.042
Variance of establishment effects	0.032	0.036	0.049	0.050	0.032	0.015
2×covariance of worker and establishment effect	0.016	0.019	0.030	0.044	0.047	0.024
Correlation of worker and establishment effect	0.135	0.150	0.181	0.243	0.321	0.093

Panel B - in % of the variance of log wages						
	Period 1 1985-1992	Period 2 1993-1999	Period 3 2000-2006	Period 4 2007-2013	Period 5 2014-2021	Change Period 2 to Period 4
Variance of worker effects	55	59	54	54	61	43
Variance of establishment effects	16	18	19	17	12	15
2×covariance of worker and establishment effect	8	10	12	15	17	25

Notes: The percentages do not add up to 100. The remaining percentages cover the unobserved $r(r_{it})$, as well as $Var(x_{it}'\beta)$ and its covariance with $\alpha_i$and $\psi_{J(i,t)}$. Sample: SIAB data, full-time workers, West Germany.

Table 3: County-level log wage inequality

Panel A						
	Period 1 1985-1992	Period 2 1993-1999	Period 3 2000-2006	Period 4 2007-2013	Period 5 2014-2021	Change Period 2 to Period 4
Variance of avg. log wages	0.0091	0.0088	0.0114	0.0138	0.0134	0.0050
Variance of worker effects	0.0021	0.0027	0.0039	0.0051	0.0063	0.0024
Variance of establishment effects	0.0028	0.0024	0.0026	0.0027	0.0018	0.0003
2×covariance of worker and establishment effect	0.0030	0.0034	0.0044	0.0054	0.0053	0.0020

Panel B - in % of the variance of county-average log wages						
	Period 1 1985-1992	Period 2 1993-1999	Period 3 2000-2006	Period 4 2007-2013	Period 5 2014-2021	Change Period 2 to Period 4
Variance of worker effects	23	30	34	37	47	48
Variance of establishment effects	31	27	23	20	13	7
2×covariance of worker and establishment effect	32	38	38	39	40	40

Notes: The percentages do not add up to 100. The remaining percentages cover the unobserved $r(r_{it})$, as well as $Var(x_{it}'\beta)$ and its covariance with $\alpha_i$and $\psi_{J(i,t)}$. Sample: SIAB data, full-time workers, West Germany.

Table 4: Decomposition of changes in colocation

Panel A: Colocation				
Year	1988	1998	2008	2018
Covariance (x100)	0.147	0.163	0.276	0.257

Panel B: Decomposition of changes in colocation by Equation 3			
	1988-1998	1998-2008	2008-2018
Change in covariance (x100)	0.017	0.113	-0.019
Worker component (x100)	0.032	0.119	0.026
Establishment component (x100)	-0.011	-0.006	-0.040
Cross-component (x100)	-0.004	-0.000	-0.005
Worker component (%)	190	106	-139
Establishment component (%)	-68	-6	214
Cross-component (%)	-22	0	25

Panel C: Shift-share decomposition of changes in the worker effect by Equation 4			
	1988-1998	1998-2008	2008-2018
Change in worker effect (x100)	-0.13	-1.63	-0.03
County stayer	3.71	2.96	5.08
Mobility (in & out)	-3.58	-4.59	-5.11
In-Mobility	-7.28	-6.25	-8.78
Out-Mobility	3.45	1.65	3.67

Panel D: Shift-share decomposition of changes in colocation by Equation 5			
	1988-1998	1998-2008	2008-2018
Change in covariance (x100)	0.017	0.113	-0.019
Contribution establishment effect (x100)	-0.011	-0.006	-0.040
Contribution worker effect (x100)			
County stayer	0.046	0.167	0.100
Mobility (in & out)	-0.014	-0.048	-0.075
In-Mobility	0.009	-0.014	-0.051
Out-Mobility	-0.024	-0.034	-0.023
Contribution cross-components (x100)	-0.004	-0.000	-0.005

Sample: SIAB data, full-time workers, West Germany.

Table 5: Trade exposure and AKM worker effect

	(1)	(2)	(3)
Import exposure (Eastern Europe + China)	-0.471***	-0.271***	-0.340***
Export exposure (Eastern Europe + China)	0.860***	1.000***	0.990***
Rurality 1998		0.008	0.010
Population 1998		0.017**	0.023**
Unemployment 1998		-0.155*	0.009
Average age 1998		-0.713**	-0.655**
College share 1998		0.436***	0.409***
Manufacturing share1998		-0.091**	-0.104***
State fixed effects	No	No	Yes
R-squared	0.103	0.382	0.428
N	324	324	324

Notes: County-level IV regressions in first differences. The dependent variable is the 1998–2008 change in the average AKM worker effect (scaled ×100). Import and export exposure are measured as 1998–2008 changes per manufacturing worker (in €1,000). Rurality ranges from 0–100; population is in 10,000s; age in years; unemployment, college share, and manufacturing employment share in percentage points. Robust standard errors reported; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Dependent variable mean = –1.63, SD = 3.8. Sample: SIAB data, full-time workers, West Germany.

Table 6: Trade exposure and AKM worker effect by trade partner and county type

	Export exposure	Import exposure
Baseline (as Table 5, Column 3)	0.990***	-0.340***
Eastern Europe	1.947***	-1.801***
China	1.831*	-0.258*
	Eastern Europe, ex ante high-paying counties	
All workers	1.987***	-2.171***
1st tercile	0.337	-0.657
2nd tercile	2.731***	-2.662***
3rd tercile	2.900***	-3.222***
	Eastern Europe, ex ante low-paying counties	
All workers	0.027	-0.000
1st tercile	0.135	-0.183
2nd tercile	-0.103	0.219
3rd tercile	0.021	-0.027

Notes: As Table 5. Estimates at the terciles pertain to the mean worker effect of the respective worker effect tercile at the county level. See main text for further details.

Table 7: Trade exposure and Covariance contribution

	(1)	(2)	(3)
Import exposure (Eastern Europe + China)	-0.022**	-0.015	-0.015
Export exposure (Eastern Europe + China)	0.038***	0.048**	0.041**
Rurality 1998		0.001*	0.001
Population 1998		-0.002**	-0.002
Unemployment 1998		0.002	0.001
Average age 1998		-0.022	-0.024
College share 1998		0.022**	0.023**
Manufacturing share1998		-0.005	-0.002
State fixed effects	No	No	Yes
Constant	0.001	0.725	0.856
R-squared	0.059	0.142	0.196
N	324	324	324

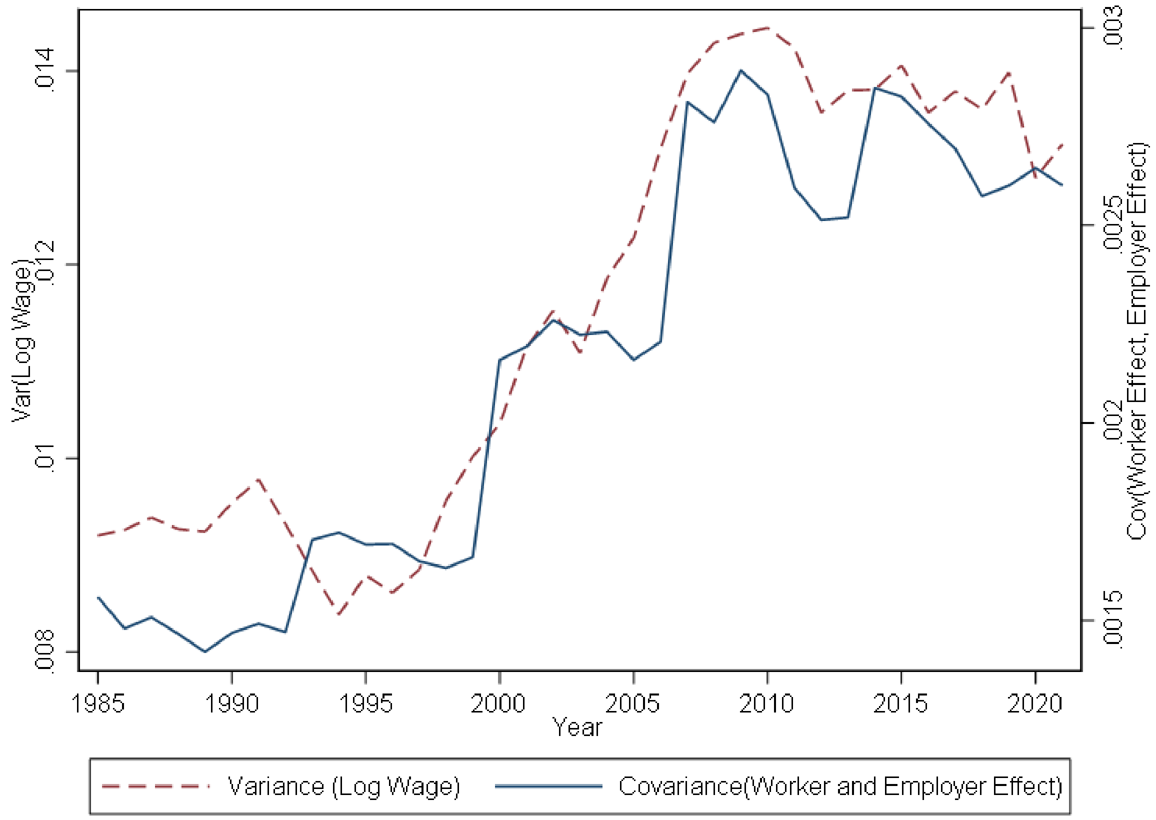
Notes: County-level IV regressions in first differences. The dependent variable is the 1998–2008 covariance contribution of a county (scaled ×100 × 324). The scaling with 324 expresses each variable's average contribution to the total change in covariance in West Germany whereas scaling with 100 just improves readability of the results. Import and export exposure are measured as 1998–2008 changes per manufacturing worker (in €1,000). Rurality ranges from 0–100; population is in 10,000s; age in years; unemployment, college share, and manufacturing employment share in percentage points. Robust standard errors reported; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$ Sample: SIAB data, full-time workers, West Germany.

Table 8: Trade exposure and Covariance contribution by trade partner and county type

	Export exposure	Import exposure
Baseline (as Table 7, Column 3)	0.041**	-0.015
Eastern Europe	0.152***	-0.155***
China	-0.109	-0.027*
	Ex ante high-paying counties	
Eastern Europe	0.083***	-0.086***
	Ex ante low-paying counties	
Eastern Europe	-0.039	0.023

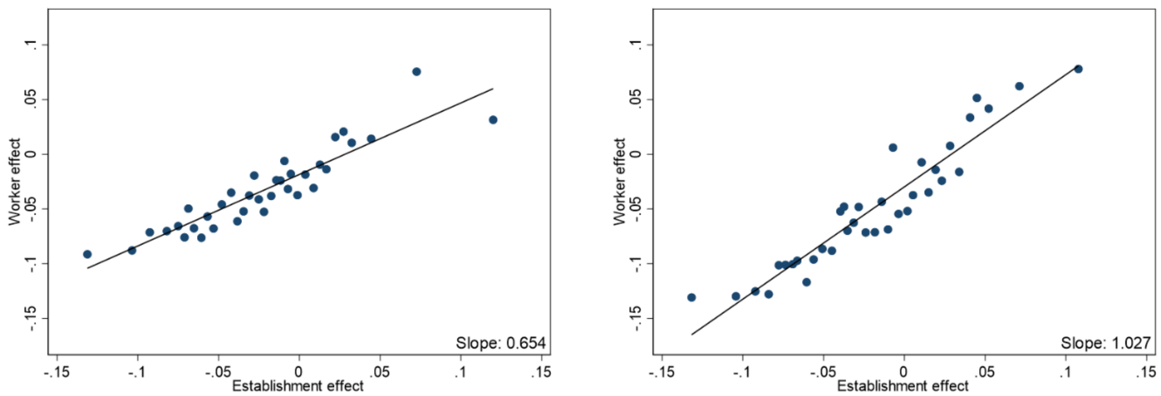
Notes: As Table 7.

Figure 1: Evolution of spatial inequality and colocation



Note: The graph shows the evolution of the between-county variance of log wages (left vertical axis) and the evolution of the between-county covariance of average AKM worker and establishment effects for 324 West German counties.

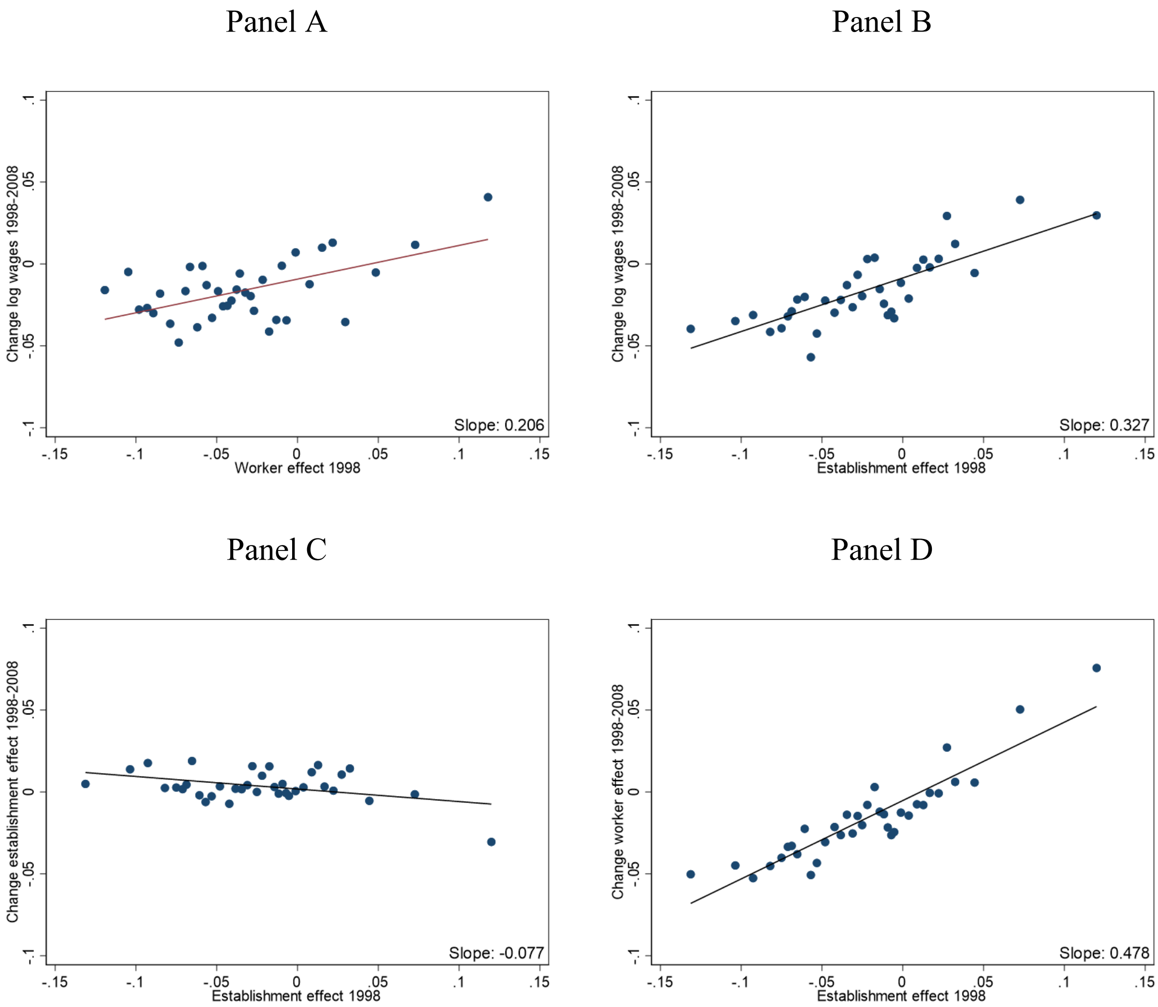
Figure 2: Increasing colocation 1998-2008



Panel A: 1998 Panel B: 2008

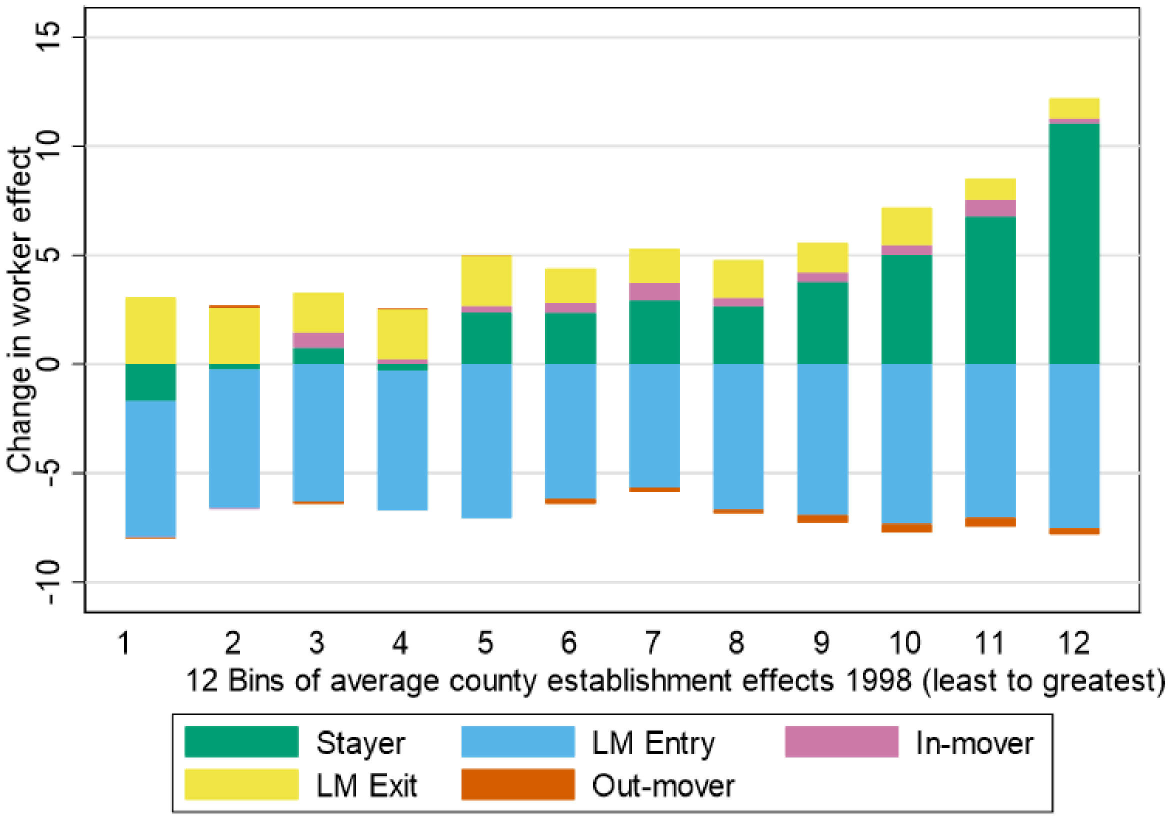
Note: The bin scatter plots are estimated using 36 bins, each containing 9 counties, totaling 9×36 = 324 West German counties.

Figure 3: Mechanisms behind increasing colocation 1998-2008



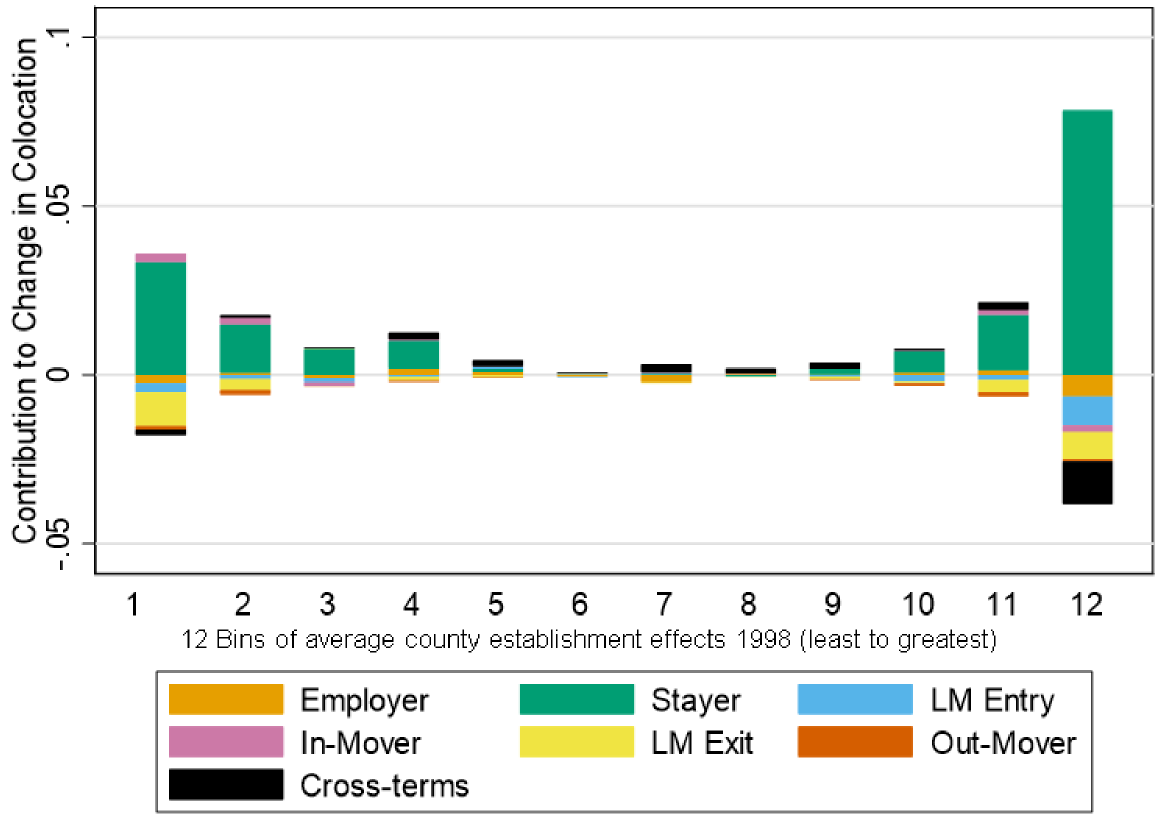
Note: The bin scatter plots are estimated using 36 bins, each containing 9 counties, totaling 9×36 = 324 West German counties.

Figure 4: Shift-share components by initial establishment effects



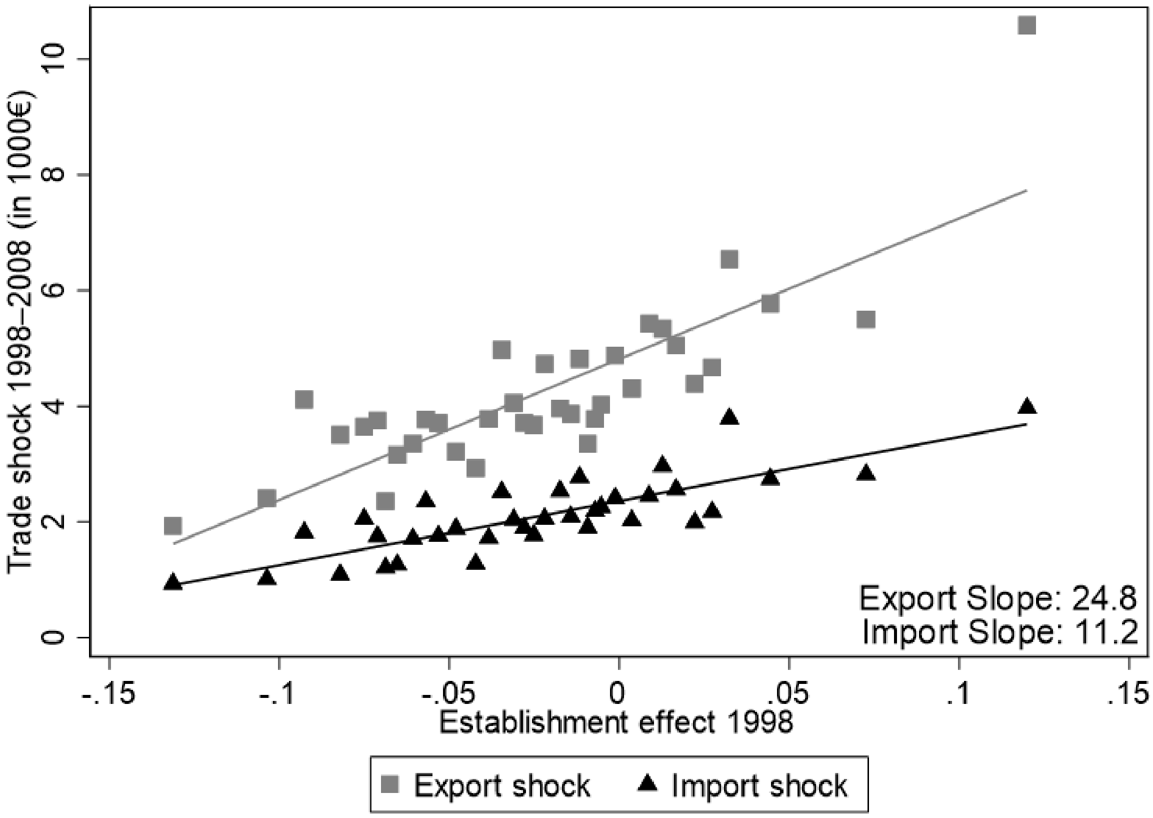
Note: The shift-share decomposition of the 1998–2008 change in county-level average worker effects is shown for 12 equal-sized bins of the 1998 county-level employer-effect distribution.

Figure 5: Colocation contributions of shift-share components by initial establishment effects



Note: The colocation contribution of the shift-share components of the 1998–2008 change in county-level average worker effects is shown for 12 equal-sized bins of the 1998 county-level employer-effect distribution.

Figure 6: Export and import growth by initial establishment effects



Note: County-level changes in exports and imports (in €1,000 per manufacturing worker) plotted against the 1998 employer-effect distribution.

Appendix A: Shift Share Analysis and Covariance decomposition

Appendix A shows in more detail the derivations used in Section 3.2. We begin with the shift-share decomposition of worker effects. This is followed by a covariance decomposition that uses the shift-share components.

Shift–Share Decomposition for the Change in the Average Worker Effect

For a county c and two years $t_0 = 1998$, $t_1 = 2008$ we partition individuals into five mutually exclusive groups:

- Stayers (S): in county c in 1998 and 2008
- Labor market entrants or returns (IE): in county c in 2008, not in the data 1998
- In-movers (IM): in county c in 2008, in another county in 1998
- Labor market exits (OX): in county c in 1998, not in the data 2008
- Out-movers (OM): in county c in 1998, in another county in 2008.

Let $N_S, N_{IE}, N_{IM}, N_{OX}, N_{OM}$ be their counts. Then $N_{1998} = N_S + N_{OX} + N_{OM}$ and $N_{2008} = N_S + N_{IE} + N_{IM}$. We can write the average county-level worker effects in base year and target year as follows:

$$\overline{\alpha}_c^{1998} = \frac{N_S \cdot \overline{\alpha}_S^{1998} + N_{OX} \cdot \overline{\alpha}_{OX}^{1998} + N_{OM} \cdot \overline{\alpha}_{OM}^{1998}}{N_{1998}}$$

$$\overline{\alpha}_c^{2008} = \frac{N_S \cdot \overline{\alpha}_S^{2008} + N_{IE} \cdot \overline{\alpha}_{IE}^{2008} + N_{IM} \cdot \overline{\alpha}_{IM}^{2008}}{N_{2008}}$$

We are interested in decomposing the difference between the two:

$$\Delta\overline{\alpha}_c = \overline{\alpha}_c^{2008} - \overline{\alpha}_c^{1998}$$

We factor out stayer baselines year-by-year by adding and subtracting, resulting in:

$$\overline{\alpha}_c^{2008} = \overline{\alpha}_S^{2008} + \frac{N_{IE}}{N_{2008}}\left(\overline{\alpha}_{IE}^{2008} - \overline{\alpha}_S^{2008}\right) + \frac{N_{IM}}{N_{2008}}\left(\overline{\alpha}_{IM}^{2008} - \overline{\alpha}_S^{2008}\right)$$

and

$$\overline{\alpha}_c^{1998} = \overline{\alpha}_S^{1998} + \frac{N_{OX}}{N_{1998}}\left(\overline{\alpha}_{OX}^{1998} - \overline{\alpha}_S^{1998}\right) + \frac{N_{OM}}{N_{1998}}\left(\overline{\alpha}_{OM}^{1998} - \overline{\alpha}_S^{1998}\right)$$

Subtracting these two expressions from each other and rearranging yields the final expression displayed in section 3.2:

$$\Delta\overline{\alpha}_c = \overline{\alpha}_C^{2008} - \overline{\alpha}_C^{1998} = \left(\overline{\alpha}_S^{2008} - \overline{\alpha}_S^{1998}\right) +$$

$$\frac{N_{IE}}{N_{2008}}\left(\overline{\alpha}_{IE}^{2008} - \overline{\alpha}_S^{2008}\right) + \frac{N_{IM}}{N_{2008}}\left(\overline{\alpha}_{IM}^{2008} - \overline{\alpha}_S^{2008}\right)$$

$$- \frac{N_{OX}}{N_{1998}}\left(\overline{\alpha}_{OX}^{1998} - \overline{\alpha}_S^{1998}\right) - \frac{N_{OM}}{N_{1998}}\left(\overline{\alpha}_{OM}^{1998} - \overline{\alpha}_S^{1998}\right).$$

Table A.1 provides additional context for Figure 4 (and, by extension, indirectly for Figure 5). It shows that workers across all five groups of the shift-share decomposition have substantially higher worker effects, higher education levels, higher employer effects, and a greater propensity to work in the manufacturing sector when employed in the 54 top-paying counties compared with the 54 counties with the lowest-paying employers. The table also shows that the 54 top-paying counties are much larger in terms of employment than the 54 lowest-paying counties. Although cross-county movers make up a small group, their moves are directed toward higher-paying locations. Moreover, the share of college-educated workers among both groups of in-movers is much higher in the top counties, and this county gap in college attainment exceeds the gap among stayers.

Covariance decomposition

We aim to decompose the change in the cross-county covariance between mean worker and employer effects:

$$\Delta \mathrm{Cov} = \mathrm{Cov}(\overline{\alpha}_c^{2008}, \psi_c^{2008}) - \mathrm{Cov}(\overline{\alpha}_c^{1998}, \overline{\psi}_c^{1998})$$

We apply the identity

$$\Delta \mathrm{Cov} = \mathrm{Cov}(\overline{\alpha}_c^{1998}, \Delta\overline{\psi}_c) + \mathrm{Cov}(\Delta\overline{\alpha}_c, \overline{\psi}_c^{1998}) + \mathrm{Cov}(\Delta\overline{\alpha}_c, \Delta\overline{\psi}_c)$$

where $\Delta\overline{\psi}_c = \overline{\psi}_c^{2008} - \overline{\psi}_c^{1998}$. Next, we insert the exact five-component shift-share decomposition of $\Delta\overline{\alpha}_c$(see above) and get the full eleven-term decomposition:

$$\Delta\text{Cov}(\overline{\alpha}_c, \overline{\psi}_c) = \text{Cov}(\overline{\alpha}_c^{1998}, \Delta\overline{\psi}_c)$$
$$+\text{Cov}\left(\overline{\alpha}_S^{2008} - \overline{\alpha}_S^{1998}, \overline{\psi}_c^{1998}\right)$$
$$+\text{Cov}\left(\frac{N_{IE}}{N_{2008}}\left(\overline{\alpha}_{IE}^{2008} - \overline{\alpha}_S^{2008}\right), \overline{\psi}_c^{1998}\right)$$
$$+\text{Cov}\left(\frac{N_{IM}}{N_{2008}}\left(\overline{\alpha}_{IM}^{2008} - \overline{\alpha}_S^{2008}\right), \overline{\psi}_c^{1998}\right)$$
$$-\text{Cov}\left(\frac{N_{OX}}{N_{1998}}\left(\overline{\alpha}_{OX}^{1998} - \overline{\alpha}_S^{1998}\right), \overline{\psi}_c^{1998}\right)$$
$$-\text{Cov}\left(\frac{N_{OM}}{N_{1998}}\left(\overline{\alpha}_{OM}^{1998} - \overline{\alpha}_S^{1998}\right), \overline{\psi}_c^{1998}\right)$$
$$+\text{Cov}\left(\overline{\alpha}_S^{2008} - \overline{\alpha}_S^{1998}, \overline{\psi}_c^{2008} - \overline{\psi}_c^{1998}\right)$$
$$+\text{Cov}\left(\frac{N_{IE}}{N_{2008}}\left(\overline{\alpha}_{IE}^{2008} - \overline{\alpha}_S^{2008}\right), \overline{\psi}_c^{2008} - \overline{\psi}_c^{1998}\right)$$
$$+\text{Cov}\left(\frac{N_{IM}}{N_{2008}}\left(\overline{\alpha}_{IM}^{2008} - \overline{\alpha}_S^{2008}\right), \overline{\psi}_c^{2008} - \overline{\psi}_c^{1998}\right)$$
$$-\text{Cov}\left(\frac{N_{OX}}{N_{1998}}\left(\overline{\alpha}_{OX}^{1998} - \overline{\alpha}_S^{1998}\right), \overline{\psi}_c^{2008} - \overline{\psi}_c^{1998}\right)$$
$$-\text{Cov}\left(\frac{N_{OM}}{N_{1998}}\left(\overline{\alpha}_{OM}^{1998} - \overline{\alpha}_S^{1998}\right), \overline{\psi}_c^{2008} - \overline{\psi}_c^{1998}\right)$$

The cross-terms (last five lines) turn out to be small empirically and we sum them into one single number in Figure 4 and Figure 5.

Appendix B: Labor Market Regions

Appendix Tables B.1 and B.2 as well as Appendix Figures B.1-B.3 document the rise in colocation at the level of labor market regions instead of counties to test whether the level of aggregation changes our insights. Labor market regions are classified by the Federal Institute for Research on Building, Urban Affairs and Spatial Development. Labor market regions are functional spatial units that contain the centers of regional labor markets and their commuting zones. They are delineated on the basis of commuting flows between counties, subject to additional restrictions: regions should respect county and federal-state boundaries, have to avoid overlaps, achieve employment self-containment rates above 65 percent, and imply one-way commuting times of no more than 45 minutes.

Appendix C: Background on trade patterns with China and Eastern Europe

To better understand Germany's trade relationships with Eastern Europe and China between 1998 and 2008, we use the BACI dataset by Gaulier and Zignago (2010). Based on United Nations Comtrade data, this dataset covers international trade at the product level from 1996 to 2023 and reports trade values in thousand USD using the Harmonized System (HS) at the 6-digit level. Our analysis focuses on German trade flows with China and a group of 21 Eastern European countries, as defined in Dauth et al. (2014). Trade values are converted into billions of euros and adjusted for inflation using the Consumer Price Index (CPI), with 2015 as the base year.

We incorporate product-level classifications using the Broad Economic Categories (BEC) system developed by the United Nations (1989), with a concordance provided by the World Bank. This allows us to categorize trade into primary and processed goods, and further into groups such as food and beverages, industrial supplies, fuels, capital goods, transport equipment, and consumer goods. Additionally, we use a second concordance from the World Bank to map HS codes to ISIC Rev. 3 industry codes. Aggregating trade at the ISIC level enables analysis by R&D intensity, following the OECD (2003) classification.

Table C.1 illustrates the growth in Germany's trade with Eastern Europe and China discussed in the main text. Figure C.1 decomposes this growth by R&D intensity and BEC classification. The R&D decomposition shows that German trade with Eastern Europe (Panel A) is more skewed toward high-tech goods compared to China (Panel B). While trade with China increased across all R&D groups, Germany exports significantly more high-tech goods to Eastern Europe and imports more high-tech goods from the region. In contrast, German imports from China are more heavily concentrated in low-tech goods.

The BEC breakdown in Panels C and D offers further insight. Panel C shows that intermediate goods dominate trade with Eastern Europe, with nearly balanced flows suggesting deep economic integration. In contrast, trade with China is primarily composed of imports of consumer goods. Panels E and F distinguish between primary and processed goods within food and beverages, industrial supplies, and fuels. Germany primarily imports raw materials from Eastern Europe and exports processed goods in return— a pattern not seen with China. Trade with China involves minimal primary goods and is instead dominated by net imports of processed, capital, and consumer goods.

In sum, the analysis highlights that Germany's trade with Eastern Europe is more skill- and technology-intensive than its trade with China. It suggests a pattern in which Germany imports primary goods like fuels from Eastern Europe, processes them domestically, and re-exports higher-value products. By contrast, trade with China is more oriented toward imports of finished goods.

Appendix D: Computing a county´s contribution to changes in colocation

This appendix shows how the county-level contribution to the change in colocation is derived and provides intuition for the rescaling used in the main regressions. We define the cross-county covariance between average worker and establishment effects in period t as:

$$Cov_t(\bar{\alpha},\bar{\psi}) = \frac{1}{C}\sum_{c=1}^{C}\left(\bar{\alpha}_{c,t} - \bar{\bar{\alpha}}_{c,t}\right)\left(\bar{\psi}_{c,t} - \bar{\bar{\psi}}_{c,t}\right)$$

where $\bar{\alpha}_{c,t}$ and $\bar{\psi}_{c,t}$ denote county means and $\bar{\bar{\alpha}}_{c,t}$, $\bar{\bar{\psi}}_{c,t}$ are the national means. A county's contribution is simply the summand inside this expression divided by C = 324. The change in its contribution between t-1 and t is therefore:

$$\Delta Contribution_c = \frac{1}{C}\left(\bar{\alpha}_{c,t} - \bar{\bar{\alpha}}_{c,t}\right)\left(\bar{\psi}_{c,t} - \bar{\bar{\psi}}_{c,t}\right) - \frac{1}{C}(\bar{\alpha}_{c,t-1} - \bar{\bar{\alpha}}_{c,t-1})(\bar{\psi}_{c,t-1} - \bar{\bar{\psi}}_{c,t-1})$$

Summing these changes across counties yields the aggregate change in covariance. Using 1/C rather than 1/(C-1) ensures that county-level contributions add up exactly to the overall moment. The expression also makes clear that each county enters with the same weight irrespective of its size.

We multiply the trade exposure coefficients with C (and by 100 for readability). This rescaling has no effect on relative magnitudes across counties but makes the regression coefficients easier to interpret. With the scaling (and by assuming homogenous treatment effects across counties), coefficients can be read directly as the contribution of a trade shock on the total change in colocation.

Appendix References

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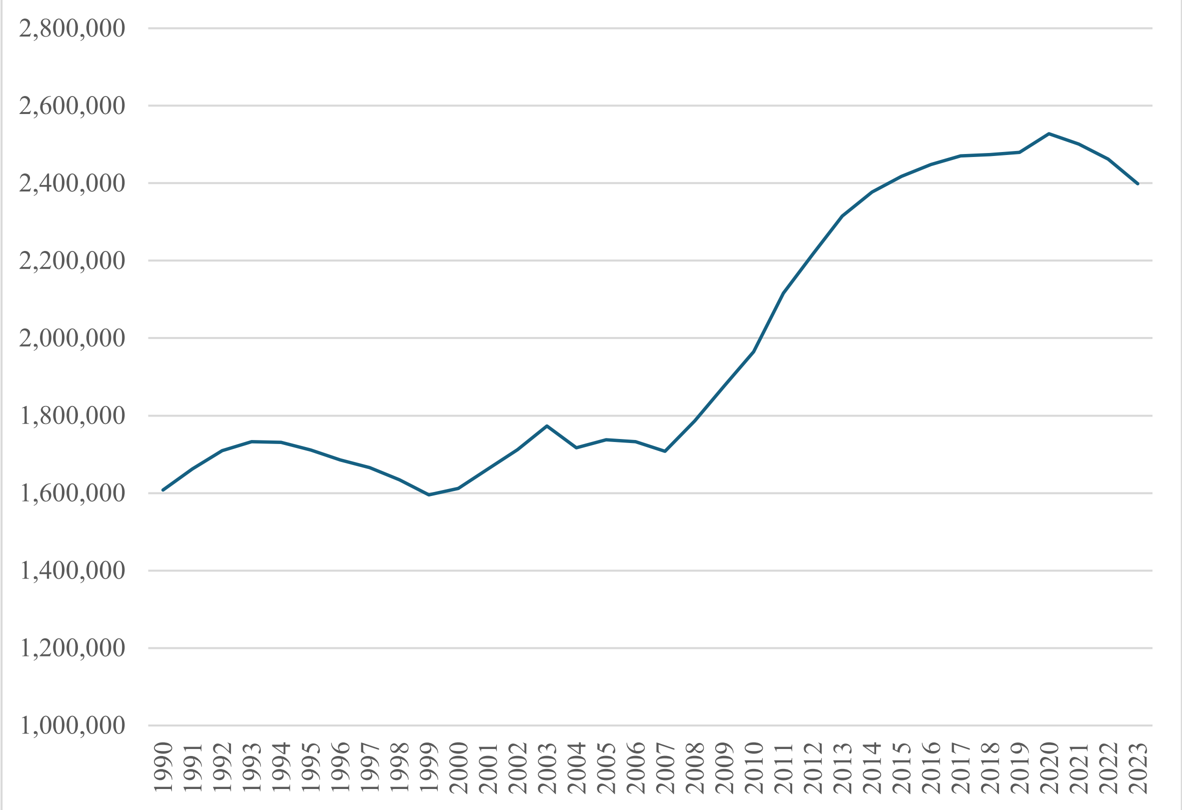
Appendix Tables and Figures

Table A.1: County-level descriptive statistics on shift-share subgroups

	Position in the distribution of 1998 establishment effects		
	Bottom sixth (54)	Middle (216)	Top sixth (54)
Panel A: Stayers (2008)			
Worker effect 2008	-0.058	0.003	0.123
Establishment effect 2008	-0.040	0.029	0.107
Average age	45.77	46.00	46.14
Share <= 30 years	0.009	0.006	0.006
Share >= 55 years	0.145	0.149	0.143
Female (0/1)	0.242	0.256	0.238
College (0/1)	0.050	0.079	0.136
Manufacturing (0/1)	0.371	0.435	0.487
# of workers	9,300	72,034	38,787
Panel B: Cross-county in-movers (2008)			
Worker effect 2008	-0.056	0.004	0.147
Establishment effect 2008	-0.070	-0.002	0.058
Average age	43.66	43.82	43.53
Share <= 30 years	0.014	0.013	0.011
Share >= 55 years	0.085	0.090	0.081
Female (0/1)	0.226	0.210	0.209
College (0/1)	0.128	0.180	0.256
Manufacturing (0/1)	0.273	0.336	0.323
# of workers	2,912	23,705	16,070
Panel C: Labor market entry (2008)			
Worker effect 2008	-0.201	-0.148	-0.044
Establishment effect 2008	-0.135	-0.076	-0.008
Average age	34.23	33.93	33.76
Share <= 30 years	0.485	0.490	0.479
Share >= 55 years	0.039	0.036	0.031
Female (0/1)	0.412	0.412	0.391
College (0/1)	0.093	0.128	0.202
Manufacturing (0/1)	0.266	0.287	0.286
# of workers	9,814	73,502	44,991
Panel D: Cross-county out-movers (1998)			
Worker effect 1998	-0.047	-0.007	0.056
Establishment effect 1998	-0.093	-0.025	0.053
Average age	33.16	33.37	33.60
Share <= 30 years	0.397	0.378	0.360
Share >= 55 years	0.000	0.000	0.000
Female (0/1)	0.213	0.215	0.217
College (0/1)	0.008	0.126	0.201
Manufacturing (0/1)	0.299	0.330	0.340
# of workers	2,937	24,752	14,998

Panel E: Labor market exit (1998)			
Worker effect 1998	-0.107	-0.061	0.013
Establishment effect 1998	-0.093	-0.025	0.053
Average age	41.18	42.00	43.21
Share <= 30 years	0.242	0.229	0.197
Share >= 55 years	0.160	0.175	0.193
Female (0/1)	0.440	0.426	0.391
College (0/1)	0.051	0.074	0.118
Manufacturing (0/1)	0.290	0.331	0.372
# of workers	11,087	83,266	48,600

Figure A.1: Number of Germans enrolled in tertiary education



Source: German Federal Statistical Office. https://www.destatis.de/EN/Themes/Society-Environment/Education-Research-Culture/Institutions-Higher-Education/Tables/lrbil01.html#242476 (retrieved March 2025)

Table B.1: Labor market region-level log wage inequality

Panel A						
	Period 1 1985-1992	Period 2 1993-1999	Period 3 2000-2006	Period 4 2007-2013	Period 5 2014-2021	Change Period 2 to Period 4
Variance of avg. log wages	0.0078	0.0067	0.0085	0.0105	0.0102	0.0035
Variance of worker effects	0.0015	0.0018	0.0026	0.0035	0.0043	0.0017
Variance of establishment effects	0.0024	0.0019	0.0022	0.0023	0.0016	0.0004
2×covariance of worker and establishment effect	0.0023	0.0026	0.0033	0.0042	0.0041	0.0016

Panel B - in % of the variance of labor-market-region-average log wages						
	Period 1 1985-1992	Period 2 1993-1999	Period 3 2000-2006	Period 4 2007-2013	Period 5 2014-2021	Change Period 2 to Period 4
Variance of worker effects	21	27	31	33	42	49
Variance of establishment effects	34	29	25	22	16	11
2×covariance of worker and establishment effect	32	38	39	40	41	46

Notes: The percentages do not add up to 100. The remaining percentages cover the unobserved $r(r_{it})$, as well as $Var(x_{it}'\beta)$ and its covariance with $\alpha_i$and $\psi_{J(i,t)}$. Sample: SIAB data, full-time workers, West Germany.

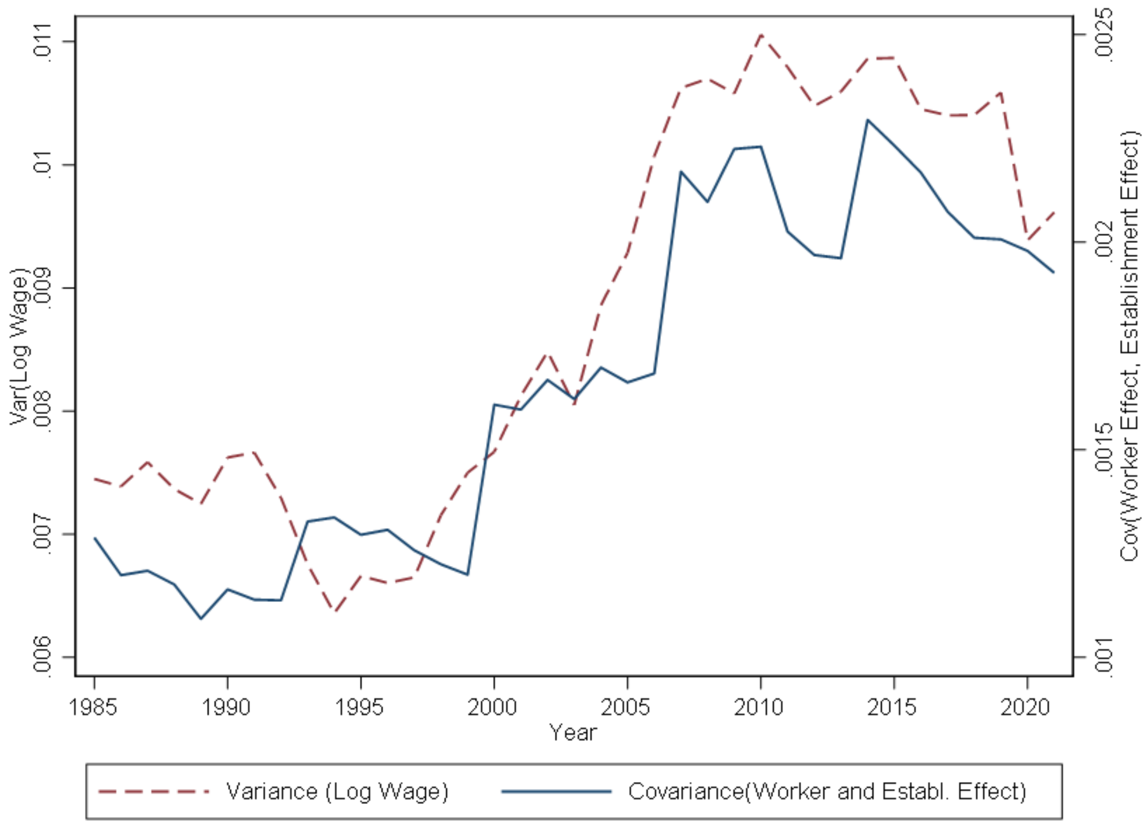
Table B.2: Decomposition of changes in colocation at the level of labor market regions

Panel A: Colocation				
Year	1988	1998	2008	2018
Covariance (x100)	0.118	0.122	0.210	0.201

Panel B: Decomposition of changes in colocation by Equation 3			
	1988-1998	1998-2008	2008-2018
Change in covariance (x100)	0.005	0.087	-0.009
Worker component (x100)	0.026	0.097	0.024
Establishment component (x100)	-0.017	-0.006	-0.027
Cross-component (x100)	-0.004	-0.004	-0.005
Worker component (%)	528	111	-275
Establishment component (%)	-352	-7	318
Cross-component (%)	-76	-4	57

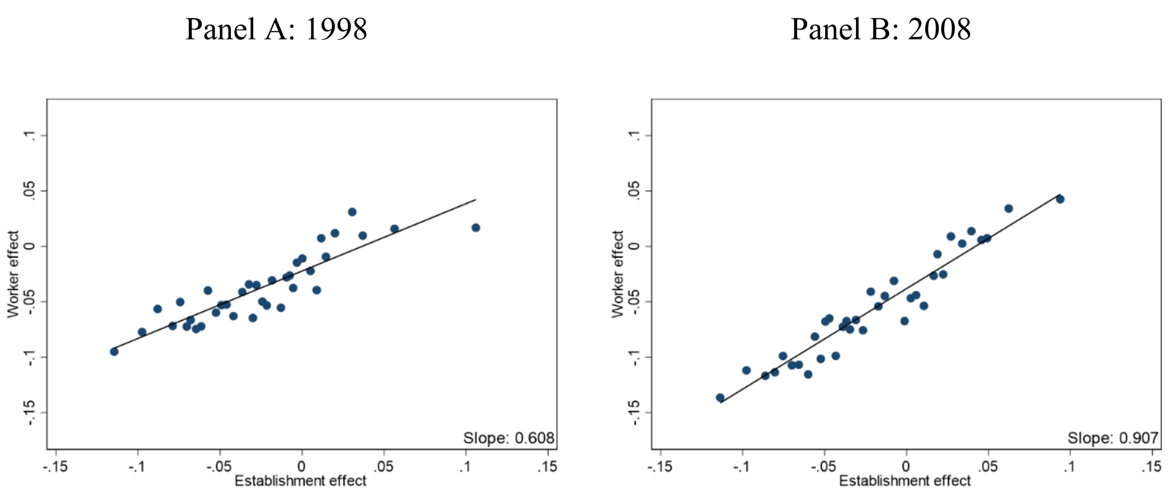
Sample: SIAB data, full-time workers, West Germany.

Figure B.1: Evolution of spatial inequality and colocation



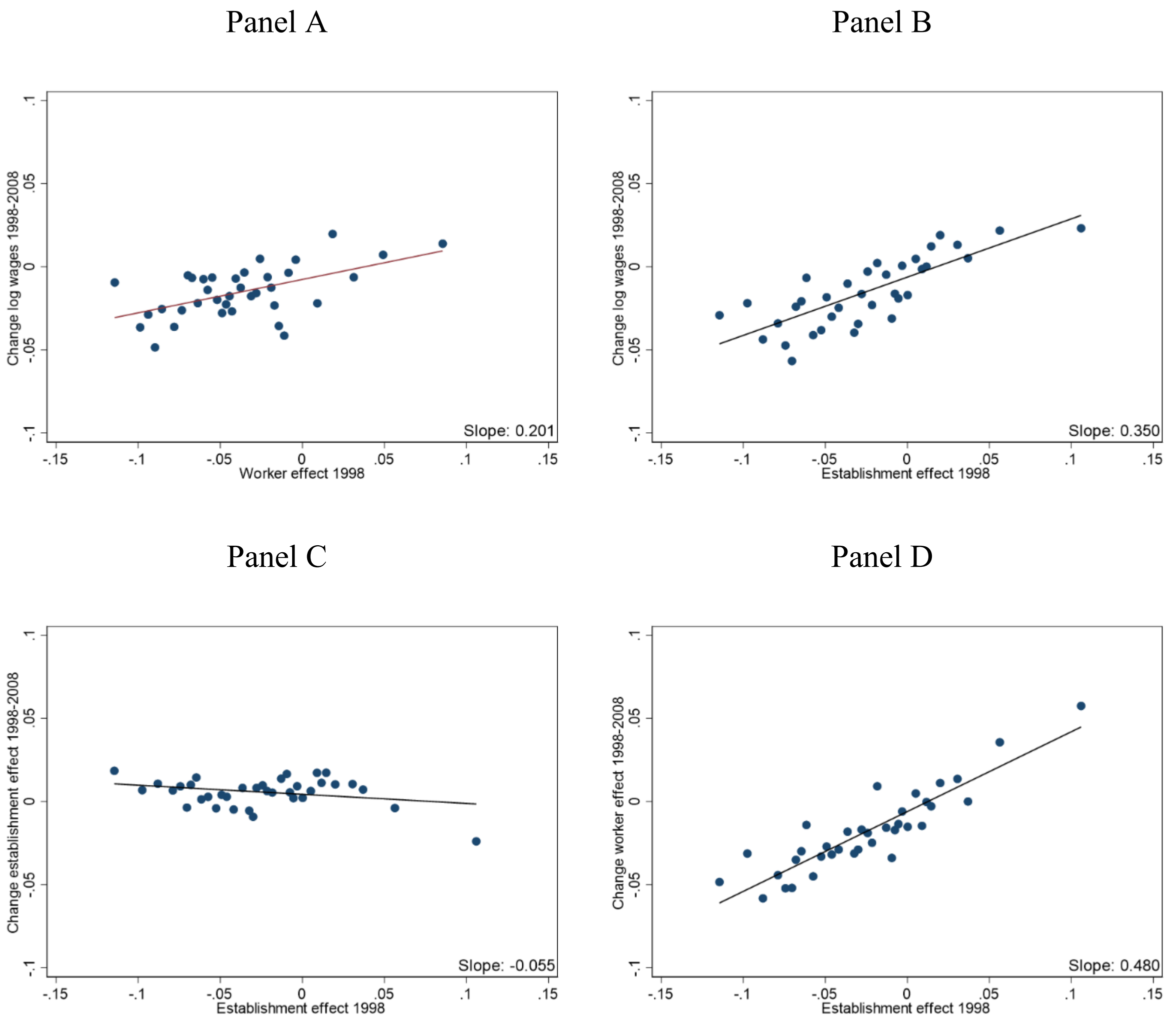
Note: The graph shows the evolution of the between-county variance of log wages (left vertical axis) and the evolution of the between-county covariance of average AKM worker and establishment effects for 203 West German labor market regions.

Figure B.7: Increasing colocation 1998-2008



Note: The bin scatter plots are estimated using 36 bins, each containing 5-6 labor market regions, totaling 203 West German labor market regions.

Figure B.3: Mechanisms behind increasing colocation 1998-2008



Note: The bin scatter plots are estimated using 36 bins, each containing 5-6 labor market regions, totaling 203 West German labor market regions.

Table C.1: German trade with Eastern Europe and China

	1998	2008	Total change 1998-2008
Panel A: Export value (in Billion Euros)			
Total Exports	68.4	198.4	130
Eastern Europe	60.8	161.6	100.8
China	7.6	36.8	29.2
County-level per manufacturing worker (in 1,000 Euro)			
Eastern Europe			4,250
China			1,209
Panel B: Import value (in Billion Euros)			
Total Imports	70.2	191.4	121.2
Eastern Europe	54.9	125.6	70.7
China	15.4	65.8	50.5
County-level per manufacturing worker (in 1,000 Euro)			
Eastern Europe			2,104
China			2,112

Notes: Euro values are CPI adjusted on (2015 = 100). BACI data, German trade with Azerbaijan, Belarus, Bulgaria, China, Czech Republic, Estonia, Georgia, Hungary, Kazakhstan, Kyrgyzstan, Latvia, Lithuania, Moldova, Poland, Romania, Russian Federation, Slovakia, Slovenia, Tajikistan, Turkmenistan, Ukraine, Uzbekistan.

Table C.2: Change in the average AKM worker effect of stayers

	(1)	(2)	(3)
Import exposure (Eastern Europe + China)	-0.587***	-0.162*	-0.237**
Export exposure (Eastern Europe + China)	1.191***	1.363***	1.352***
Rurality 1998		0.001	0.002
Population 1998		0.020**	0.026**
Unemployment 1998		-0.148*	-0.003
Average age 1998		-0.018	-0.046
College share 1998		0.575***	0.560***
Manufacturing share1998		-0.173**	-0.183***
State fixed effects	No	No	Yes
R-squared	0.080	0.545	0.595
N	324	324	324

Notes: Specification as in Table 5. The dependent variable is the 1998–2008 change in the average AKM worker effect for stayers (scaled ×100)..

Table C.3: Trade exposure and average AKM worker effect for stayers by trade partner and county type

	Export exposure	Import exposure
Baseline model (as Tab C.2, col 3)	1.352***	-0.237**
Eastern Europe, only	2.526***	-2.080***
China, only	3.052**	-0.034
	Eastern Europe, ex ante high-paying counties	
All workers	2.644***	-2.294***
	Eastern Europe, ex ante low-paying counties	
All workers	0.657	-0.650

Notes: Specification as in Table 5, column 3. The dependent variable is the 1998–2008 change in the average AKM worker effect for stayers (scaled ×100)..

Table C.4: Change in the average AKM establishment effect

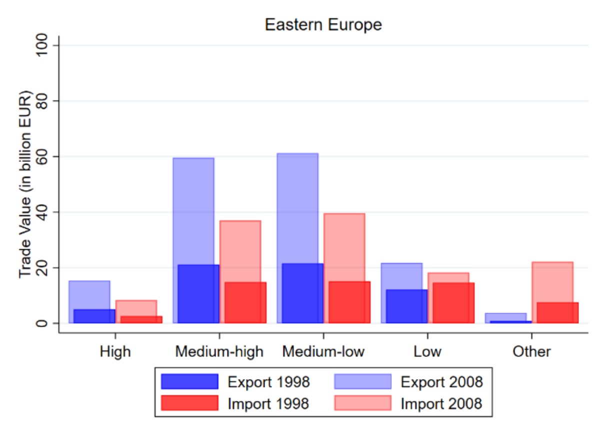
	(1)	(2)	(3)
Import exposure (Eastern Europe + China)	0.035	-0.132	-0.145*
Export exposure (Eastern Europe + China)	-0.067	-0.254	-0.236
rurality		0.004	0.013**
Population 1998		-0.020***	-0.023***
Unemployment 1998		0.014	0.133**
Avg. age 1998		-0.505***	-0.518**
College share 1998		0.140***	0.155***
Manufacturing share1998		0.106***	0.089**
State FE	No	No	Yes
R-squared	0.000	0.063	0.169
N	324	324	324

County-level IV regressions in first differences. The dependent variable is the 1998–2008 change in the average AKM establishment effect (scaled ×100). Import and export exposure are measured as 1998–2008 changes per manufacturing worker (in €1,000). Rurality ranges from 0–100; population is in 100,000s; age in years; unemployment, college share, and manufacturing employment share in percentage points. Robust standard errors reported; *** p < 0.01, ** p < 0.05, * p < 0.10. Sample: SIAB data, full-time workers, West Germany.

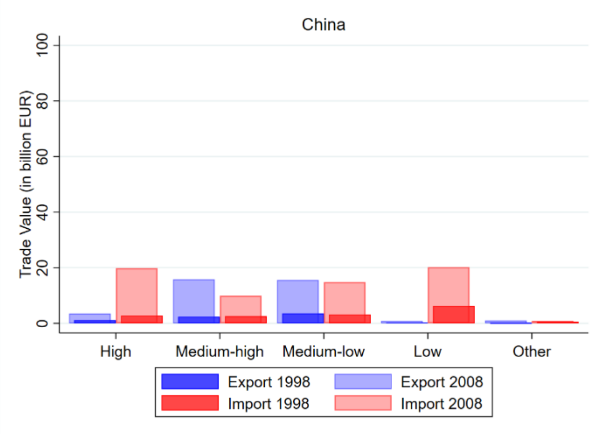
Figure C.1: Varieties traded with Eastern Europe and China between 1998 and 2008

Decomposition by R&D intensity

Panel A

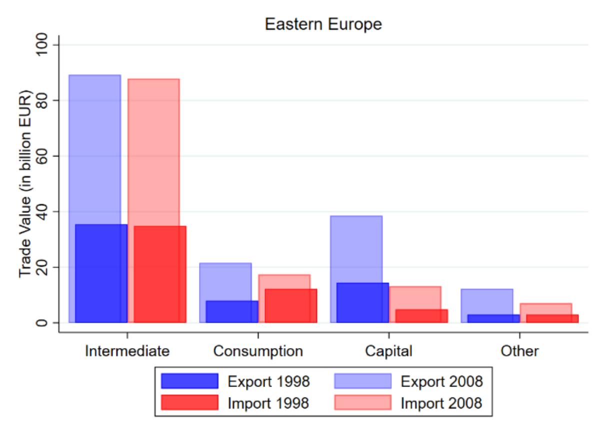


Panel B

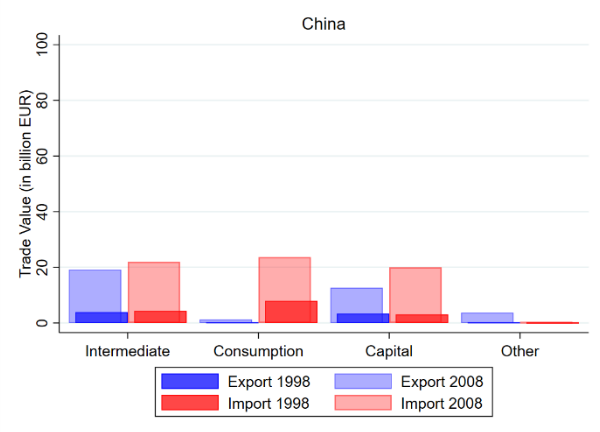


Decomposition by broad economic categories

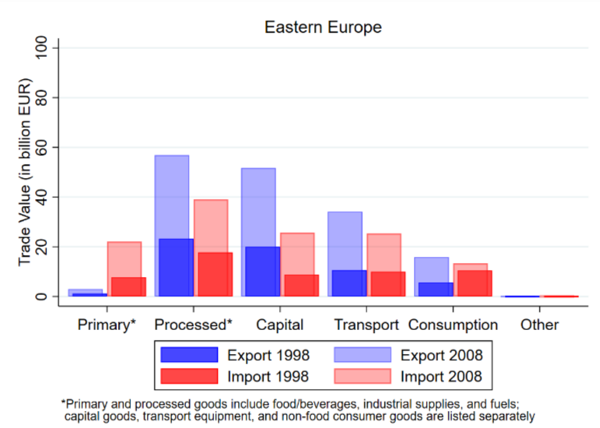
Panel C



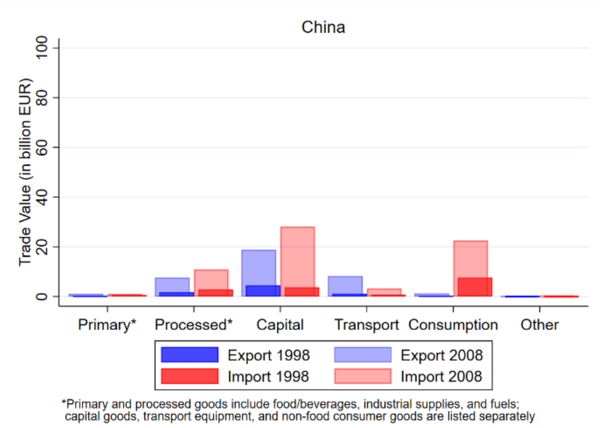
Panel D



Panel E



Panel F



Source: BACI: International Trade Database at the product-level. Conversion on ISIC Rev. 3 industry level and classified by R&D intensity and broad economic categories (BEC)

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